Abstract Dissertation

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Abstract

This paper refers to the future energy scenario of 2050, where new issues about electricity networks will arise due the changes in both the generation and the demand side. In the future more monitoring and control will be needed on distribution networks. The current techniques applicable at the transmission level are not suitable for distribution networks, thus we need to tackle the problem from a different perspective. In this paper we explore the possibility of using planning techniques to manage the operations in distribution networks.

1 Introduction

From the beginning of the XX century to nowadays the usage of electricity network experienced an incredible growth. As shown in Figure 1, from 1950 the electricity supplied in UK is quintupled. The electricity consumption is expected to further increase in the next years: the reduction of availability of fossil sources will bring to the electrification of heating and transport sectors, a radical change in the power production industry, in the current electrical infrastructure and also in the behaviour of the electricity users. All these thematics are addressed in the Autonomic Power System (APS) project, an ESPRC founded project focused on the electricity scenario of 2050 (McArthur et al. 2012).

The APS project is based on the assumption that the future energy networks will be shaped in a far more complex way and a centralised management of the operations in the electricity network, as it is now, will not be feasible anymore. Instead, a fully decentralised framework is taken as model for the future.

Among the topics studied in the project, consistent effort is spent studying the distribution networks. For example, in future many houses will have solar panels installed and necessity of charging electrical vehicles; these and numerous other aspects affect the way in which the electricity is distributed. The realisation of the automation of the decision making for distribution electricity networks is a step forward in their management which is necessary to cope with the increase in power system complexity that we expect in the near term.

My PhD project is focused on the applications of AI Planning techniques for solving problems in given zones of distributed electricity networks. The general task is to provide sufficient electricity to the users, maintaining constraints on the network, in order to prevent damage to the equipment, and minimising market cost. The behaviour of the consumers involves uncertainties, thus a risk analysis needs to be integrated.

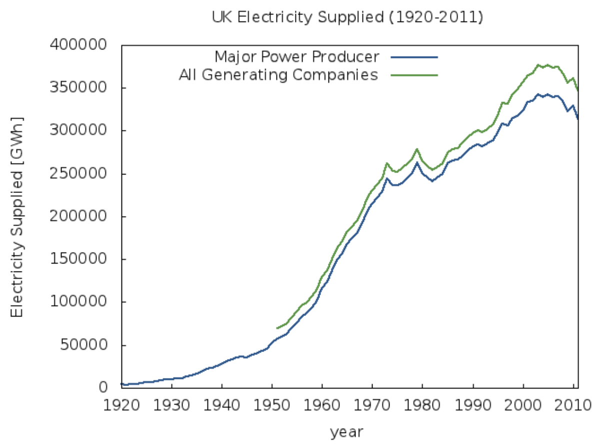

Figure 1: Electricity supplied in UK during the last century (UK Department of Energy and Climate Change 2013).

In this dissertation, I first describe the main issues of the distribution networks, then I delineate how AI Planning can be used to tackle them and I show the first progress in this direction. Finally, I sketch the plans for the future.

2 Electric Power System

An electric power system can be defined as a network of different electrical component used to supply, transmit and consume electrical power. As shown in Fig. 2, the basic components of a power system are:

- **Generation:** various units produce power from combustible fuels (coal, natural gas, biomass) or non-combustible fuels (wind, solar, nuclear, hydro power);
- **Transmission network:** is used for the bulk transfer of power over long distances and at high voltages between main load centres;
- **Distribution network:** from the transmission network the

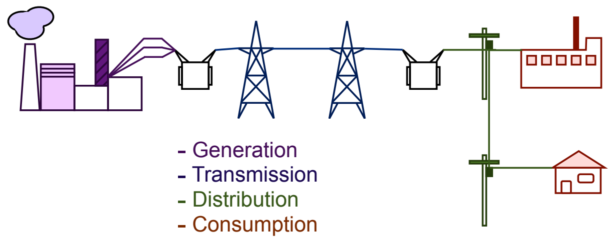

Figure 2: Power System.

power is stepped down in voltage from a transmission level voltage to a distribution level voltage;

- **Demand:** electricity is requested by industrial, commercial and domestic system users/customers.

Although transmission and distribution networks are composed by similar elements (lines, transformers, etc.) they are very different in features and operation conditions. In transmission networks, the electrical power is brought to high-voltage, thus it can be efficiently transported over long distance. On the other hand, distribution networks operate at lower voltage, because they are responsible for delivering electricity to the consumer's service entrance equipment. To reduce the risk of failures, transmission networks are interconnected into wide networks, providing multiple path for power to flow. On the contrary, distribution networks are characterised by a radial topology, therefore a customer is reached by a unique route. In transmission networks many control points are set and the data are collected and sent to some SCADA (supervisory control and data acquisition) to monitor the situation, while in distribution networks such control mechanisms are not present.

2.1 Challenges of the Future Distribution Networks

In these years the number of distributed generators connecting to the distribution networks is increasing. They are small generators that produce electricity from many small energy sources, generally located close to the site of demand, such as solar panels or small wind turbines. Their connection to the distribution networks arises new problems for the monitoring of the network. Moreover, the output of the generators can be coordinated in order to satisfy the demand with a minimum market cost.

In the future perspective, where a large number of distributed generators will be interconnected, the automation of operations of the distribution network will play an important role. The future complexity will make not feasible to solve a unique problem for the entire network, therefore a decomposition *criterion* need to be applied to solve problems for small sub-networks.

The problem that need to be addressed consists of ensuring that the electricity demands of the consumers are met by the committed supply, minimising the cost and maintaining the following constraints on the network:

- Voltage constraints: the voltage of each node (*busbar*) of the network must lie within an upper and a lower limit.
- Thermal constraints: the power flowing into the wires of the circuit can only exceed a given threshold for a constrained amount of time.

In the current framework the demand can be assumed to be predictable, but in the future scenario uncertainties arise in the demand profile, thus the solution of the problem need to be guaranteed within a given probability.

2.2 Related Works

The problem of optimising the power flow (*optimal power flow*) in an electricity network is widely explored in the engineering literature (Momoh, El-Hawary, and Adapa 1999a; 1999b). The optimal power flow is generally solved at the transmission level and in a large time-scale, thus it is not suitable for control problems in distribution networks.

An alternative approach is proposed in the AuRA-NMS project, in which the optimal power flow is formulated as a constraint satisfaction problem (*CSP*) (Davidson et al. 2009). Although the results described in the paper shown that this approach is feasible with quite small networks, there is no evidence that the model can scale well with bigger networks. Moreover they do not model voltage and thermal constraints.

In general the computational cost of such a problems is due to the load flow analysis, the calculation of the voltage magnitude and phase angle at each node of an electrical network:

$$P_i + jQ_i = \tilde{V}_i \left[\sum_{n=1}^{N} \tilde{Y}_{in} \tilde{V}_n \right]^* , \qquad (1)$$

where $\tilde{V} \in \mathbb{C}^N$ is the vector of nodal voltages, $\tilde{Y} \in \mathbb{C}^N \times \mathbb{C}^N$ is the admittance matrix, $P \in \mathbb{R}^N$ is the real power and $Q \in \mathbb{R}^N$ is the reactive power.

A standard way to simplify this equations is to consider a set of linear equation called linearised DC (*LDC*), that can capture the active power behaviours. However this model does not take into account the reactive power, therefore it cannot be used for problems involving voltage constraints. A more sophisticated approximation is presented in the paper (Coffrin et al. 2012). The non-linearity of the equation is overcome by introducing a linear-programming approximation of the AC power flow equations, using a piecewise-linear approximation of the cosine. In this formulation, the values of active and reactive power can be decision variables and the model can be embedded in a MIP solver for making discrete decisions about the power system. The weakness of this formulation comes from the non-linear behaviour of transformers, that introduce loss of accuracy in the solution of the power flow calculation.

In this dissertation we propose an approach in which we use heuristic search coupled to a root finder solver for the AC power flow equations. In the following section, this method is extensively described, pointing out the model used to described the problem, the issues that this problem arises, the solving method proposed and the first results.

```
(:durative-action step-up-gen-1
   :parameters (?g - intern-gen)
   :duration (= ?duration 1)
   :condition (and
      (at start (>= (gen-p-level ?g)
         (p-minimum-gen ?g)))
      (at start (<= (gen-p-level ?g)
         (p-maximum-gen ?g)))
      (over all (< (count-power ?g) 100)))
   :effect (and
      (at start (increase (gen-p-level ?g) 1))
      (at start (increase
         (gen-q-level ?g) 0.2))
      (forall (?g - slack-gen) (and
      (at start (decrease (ipsa-slack-p ?g) 1))
      (at start (decrease
         (ipsa-slack-q ?g) 0.2))))
      (at start (increase (count-power ?g) 1))
      (at end (decrease (count-power ?g) 1))))
```

Figure 3: Example of Action in PDDL that models a step-up of power in a generator

3 AI Planning Approach

AI Planning is a family of solving techniques that find a partially-ordered set of actions to achieve a goal state, given the initial state. A powerful tool used by modern planners is the heuristic search. It is a technique that allows to explore a search space more quickly than classic methods and it can find a feasible solution rather then optimal one, but this fact is a more desirable in control problems. AI planning can be used to model and solve the problem of management of the operations in a distributed electricity networks.

3.1 Planning Model

The language used to model this problem is PDDL2.1 (Fox and Long 2003), an extension of PDDL that allows to express numeric quantities and temporal resources.

The different elements of the network, such as generators, busbars, loads, and cables are modelled as objects in PDDL and they are specified in the initial state. At each object, fluents can be associated representing numerical variables. For example the active and reactive power generated by the power unit `gen1` can be expressed with the functions `(gen-p-level gen1)` and `(gen-q-level gen1)` respectively. The decision variables are parameterised actions. An example is shown in Fig. 3. This action describes the behaviour of a generator and it indicates that it is possible to increase the generating power of one unit, if the generator does not exceed its maximum capacity. This action has a fixed duration of one unit of time, so that we can impose a constraint on the ramp-up/down ratio of a generator. The constraint is captured with the function `(count-power ?g - generator)`, that is increased at the start of the action and decreased at its end and the condition of having a maximum ratio (100 unit in the example) is set as precondition of the action. In an analogous way, we can model the behaviour of a transformer, that has the main effect of reducing or increasing the voltage at the connected busbars.

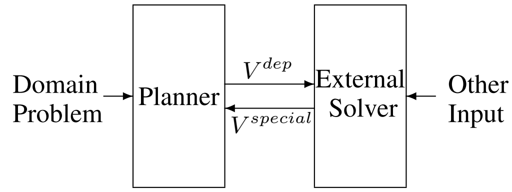

Figure 4: Scheme of the implementation of the planner and the external solver.

Global constraint that must be satisfied during the whole length of the plan, such as the voltage and the thermal constraints, are modelled with an envelope action `(constraint-check)` that is forced to start at the begging of the plan and lasts until the last change happens.

In this stage of the research we assume that the demand profile is predictable and known *a priori*. It can be modelled as a list of timed initial fluents that are completed specified in the initial state.

The final objective of the plan is to satisfy the demand deciding how much power need to be generated, maintaining the voltage and the thermal constraints. It is a temporal extended goal and it is guaranteed by the `(constraint-check)` action, so the goal state of the model is set to be the end of this action.

3.2 AI Planning Issues

This domain presents some features that make not trivial its solution.

First, some of the numeric variables cannot be easily expressed as linear functions. In particular the voltage on the busbars of the networks and the power flowing into the lines are calculated following a set of non-linear equations (Eq. 1). Second, whenever an action is applied (for example the increasing of the power produced by a generator) the effects are propagated over all the elements present in the network (local actions have global effects). This particularity makes not feasible the compilation of a look-up table to describe the possible effects of an action.

A third issue arises due to the presence of exogenous events and constraints over the entire plan trajectory. Their interaction can be taken into account in the heuristic evaluation to infer additional information.

3.3 Implementation

In order to address the issues described in the previous section we modified an existing planner adding an external solver specialised in power flow calculations, taking inspiration from the Planning Modulo Theories framework (Gregory et al. 2012). We share the same idea of having a dedicated sub-solver connected to a core-planner by means of special communication constraints. In addition we modified some aspects of the heuristic evaluation in order to take into account of the interaction of exogenous events and trajectory constraints.

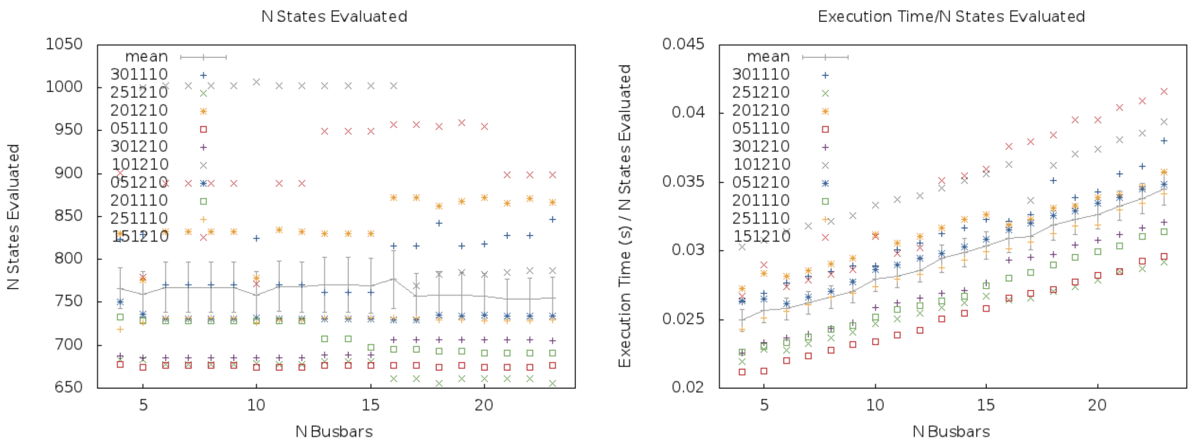

Figure 5: Results showing scaling with the number of busbars. The different points represents the different load profiles.

It should be noted that this implementation can be considered of general validity, because our external solver can be easily substituted according to the specific domain treated.

External Solver. The architecture of the external solver is shown in Figure 4.

The planner takes as input the PDDL domain and the problem files. In order to deal with the local actions with global effects and non linear functions, we divide into different categories the vectors of numeric variables in the state:

- $V^{special}$ is a vector of variables that are global numeric effects that cannot be expressed with linear functions;
- V^{dep} is a vector of variables that influence $V^{special}$;
- V^{indep} is a vector of variables that do not influence $V^{special}$.

When the planner updates a state, V^{dep} and V^{indep} are recorded. If there is a change in one of the V^{dep} variables, then the $V^{special}$ values are calculated calling the external solver, using as input all the updated values of the V^{dep} variables and other optional information of the problem. The external solver is a Newton-Raphson algorithm (Ypma 1995), an iterative numeric algorithm that allows to find successively better approximations to the zeros of a function. In order to execute the calculation, the external solver needs as input the configuration of the network (the links between the different elements) and information about resistance and impedance of wires.

The planner used in the actual implementation is POPF (Coles et al. 2010), a forward-chaining temporal planner based on a partial-ordering. Among all the temporal planners we decide to use POPF because it is the only one capable of dealing with durative actions with continuous numeric effects, negative timed initial literals and timed initial fluents. These are required to model the predictable power demand.

Heuristic. As the $V^{special}$ variables cannot be expressed as linear numeric functions, in the heuristic evaluation we use an approximation of the special functions that indicate whether an action increases, decreases or is irrelevant to $V^{special}$. The amount of increasing or decreasing of the $V^{special}$ is determined in a pre-processing stage and it is explicitly written in the PDDL model as effects of the actions on the $V^{special}$ variables.

The heuristic evaluation is modified to infer information when an exogenous event violates an active constraint: if an active action has an over all condition (c) and we have a TIL (t) and $t \rightarrow \neg c$, then the violation is inevitable. Instead, if we have a proposition s such that $t \wedge s \rightarrow \neg c$, then we must enforce $t \wedge c \rightarrow \neg s$, so that $t \rightarrow \neg s$ has to be propagated.

In our domain this situation can occur when the parameters of the load set with a timed initial fluent are such that a constraint is violated, then we infer that an action needs to be taken to bring the values within the acceptable minimum.

4 Results

In this section we present the results of experiments taken on two different problems. First we examine the management problem and we show the scalability of the planner in terms of the size of the network, while in the second part we look at the voltage problem and we evaluate domains with an increasing number of control points, showing that is possible to move towards bigger networks.

4.1 Scalability of the Size of the Network

For this evaluation we apply our implementation to decide how much power can be produced by a generator in order to satisfy the known demand during one day. Experiments are conducted with different load profiles, taken from the data set of National Grid for several winter days of 2010 (National Grid PLC 2012) and with networks with an increasing number of busbars.

The results of the experiments are summarised in Figure 5. In the left plot the number of states evaluated in function of the number of busbars (the complexity of the network) is shown and it indicates that the time spent just on the search is constant. In the right plot we show the execution time over the number of states evaluated, that can be

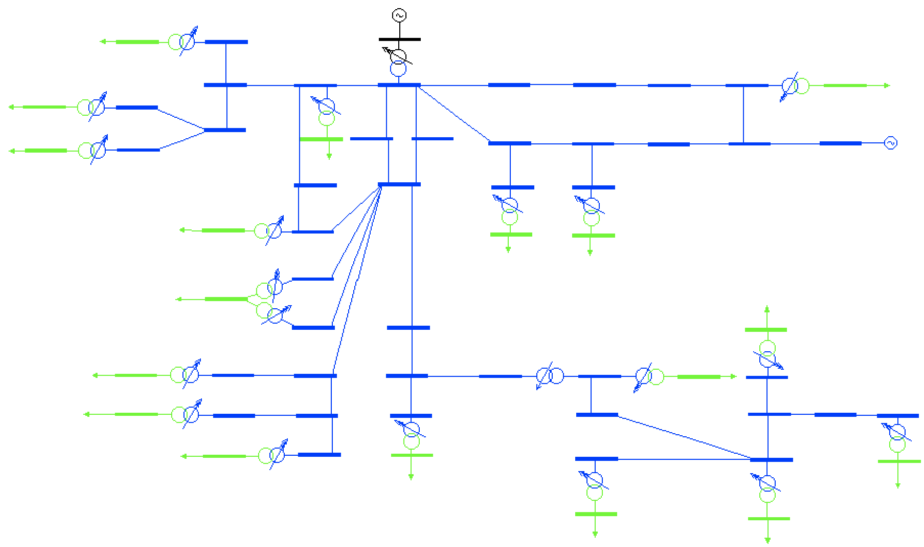

Figure 6: The small 33 kV rural network.

seen as a measure of the time spent for the evaluation of a single state, in function of the number of busbars. As we can see from the plot, the time increases with the complexity of the network, but this is not alarming because the increase is linear and the slope is small.

4.2 Scalability of the Control Points

The second evaluation that we perform is in terms of scalability of the number of control points present in the network. For this evaluation we consider the voltage control problem for the network in Figure 6. Depending on the values of the power consumed by the load, the network that we consider can suffer from voltage problems, but they can be controlled by setting a different value of the tap ratio on the appropriate transformer.

In Figure 7 we can see how the plan scales with the number of control points. In the left plot the number of states evaluated as function of the number of busbars is shown, while the right plot represents the variation of the execution times over the number of states evaluated as function of the number of transformers in the circuit. Also in this case we can see that there is a linear increase of the execution time depending on the calculation of the power flow, but the number of states evaluated is constant with respect to the number of transformers, showing essentially that the heuristic is informative enough.

5 Outlook

In this first part of my PhD I mainly focussed on having an expressive deterministic model so that we can solve planning problem within a reasonable-size zone. The main issue that this domain present is the management of temporally extended constraints and their interaction with external events.

The results show that it is possible to model and solve problems with embedded electricity network, but future work needs to be done in different directions.

First we can further improve the heuristic evaluation in order to have a better approximation of the $V^{special}$ variables. This can be done considering some linearisation of the power flow equations or using the linear programming approach proposed in the work of Ref. (Coffrin et al. 2012).

Until now we have considered the problem within a zone, but we know that zones will interact, causing uncertainties. One aspect of this will be the market effects, which will lead to cost models of actions. The cost is represented by the actual market cost of generation, that is being modelled by other partners of the APS project. We need to look at the market model to understand how it affects the planning constraints.

Also we want a robust framework for managing uncertainty, as we discuss in the following subsection.

These are topics that I will explore over the coming year.

5.1 Uncertainties

Currently the demand profiles are assumed at the outset of planning, but in fact they are subject to some variation, so the planner must be responsive to the breakdown of these assumptions when plan steps are executed.

In order to handle uncertainties we can adopt a similar approach as proposed in Ref. (Ono, Graybill, and Williams 2012). In this paper the authors use a risk-sensitive model-based plan executive in order to control the room temperature in a energy efficient way. The most significant novelty introduced in this paper is how they deal with uncertainties. They use *chance constraints* that specify a lower bound on the probability of failing, then they reformulate the stochastic constraints in deterministic terms on nominal states. The problem can be translated in term of fixed-risk planning problem that feeds an iterative algorithm *(IRA-CCQSP)*. Starting with a uniform risk allocation, at each step

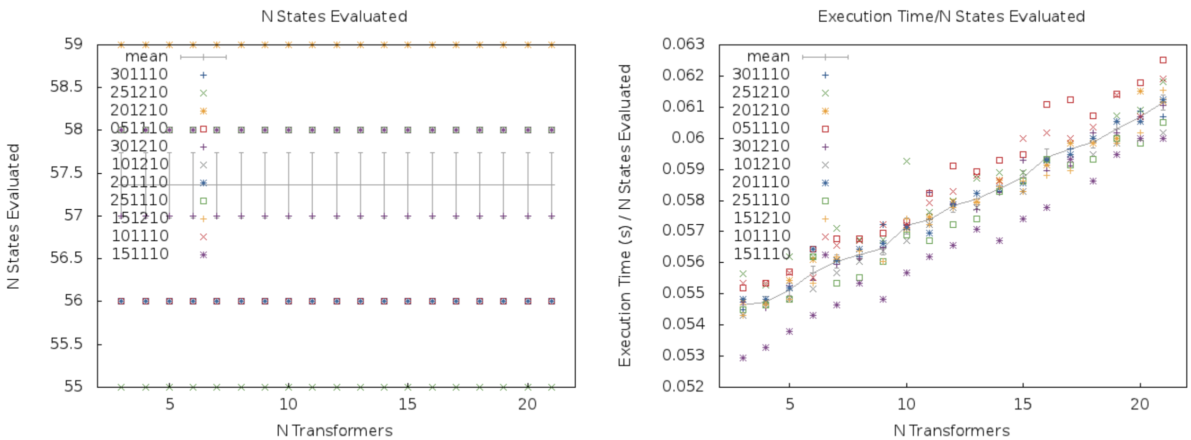

Figure 7: Results showing scaling with the number of decision points (transformers). The different points represents the different load profiles.

the algorithm solves the problem with fixed-risk and reallocates the risk for the next step.

The domain described in the paper presents the similarity of having a temporal extended goal that is controlled with a Model Predictive Control (*MPC*).

6 Conclusions

We have presented an application of planning techniques to the management of a distribution network. The task of the planner is to provide power to serve a predicted demand, respecting some constraints on elements of the network. An important difficulty of this problem is that effects propagate all over the network and they cannot be expressed in simple linear functions. We showed that planners can handle these effects using a specific solver that communicates with the planner, passing back the results of particular power flow computations. More work needs to be done in order to take into account of the market cost of power generation and, most important, to deal with the uncertainties that will be unavoidable in the future energy scenario.

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