Electrical Power and Energy Systems 63 (2014) 730–739

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Decision trees aided scheduling for firm power capacity provision by virtual power plants

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ARTICLE INFO

Article history:
Received 4 July 2013
Received in revised form 28 May 2014
Accepted 10 June 2014
Available online 15 July 2014

Keywords:
Decision trees
Distributed generation
Firm power capacity
Virtual power plant

ABSTRACT

The incorporation of Distributed Generation (DG) under the Virtual Power Plant (VPP) concept allows the market integration of several and largely dispersed electric power sources. One matter of concern for the VPP owner and operator is to follow the hourly schedule regardless of the stochastic nature of some of its sources or any unpredicted generation outages. This study presents a Decision Tree (DT) based methodology that prepares for the dispatching of power equivalent to the possible loss of the highest injection of one of the sources of the VPP (according to day-ahead hourly schedule) to the rest of its sources, on an hour-ahead horizon. This allows VPP operators to provide firm capacity and participate effectively in the energy market.

Introduction

DG has been growing rapidly and vastly due to its high efficiency compared to conventional generation [1]. Among the various DG technologies, Renewable Energy Sources (RES) are greatly favored due to their limited environmental impact [2]; notably, wind power and photovoltaics represent the core business of this trend [3,4]. However, the aforementioned RES are greatly dependent on weather and local topography, thus accounting for the intermittent and stochastic nature of the relevant DG units [5,6]. This, in turn, raises issues of less reliable power supply [7–9] and of poor power quality [10].

Power system (PS) operators and current research in the field focus on proactive and online strategies to deal with the above problems. Proactively and based on RES generation forecasts [5], power reserves are procured [8,9]. Alternatively, any excess of RES power is curtailed [11,12], while any deficit of it is balanced through load shedding coming from demand side management (DSM) [13,14]. Other balancing suggestions use active power conditioners [15] and storage devices [16]. Obviously, increasing the available PS reserves affects PS economics [11], RES curtailment discourages further penetration of sustainable generation, DSM does not essentially solve the problem and relies on load-shedding availability, while power conditioners and storage require considerable investments for large-scale applications. Lately, hybrid power stations [17] are applied as a means of RES intermittency treatment.

In order to expand the hybrid power station paradigm and, thus, also respond to all previously mentioned issues, the concept of the VPP was developed in the past few years [18,19]. There seems to be little consensus on its definition, nevertheless a concise yet broader description of its characteristics is the following: VPP is, essentially, the aggregation of any number of DGs in order either to facilitate the trading of their electric energy and/or for the purpose of jointly controlling their offer and realization of support services to the grid.

The current work deals with the problem of ensuring firm power capacity (FPC) [20] by a VPP. That is, for each hourly schedule of the VPP's power output and procured reserves available from a 24-h ahead scheduling, how should the VPP re-dispatch its resources in a fast and efficient manner in order to make up for the loss of the DG with the largest injection at the time of loss. Section 'Hypotheses and market framework' includes the hypotheses concerning the operation of the VPP in a given market framework and the problem specifics. Section 'Decision trees' offers a description of the DTs. In Section 'DT-aided scheduling methodology for FPC by VPP' the suggested technique is described. In Section 'FPC provision by VPP on Ikaria test system' the test system of Ikaria is presented and the developed strategy is tested on various scenarios. In Section 'Comments and observations on the methodology' remarks on the efficiency, speed and generalization of the technique are given. Section 'Conclusion' concludes this paper and offers ideas for future work.

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http://dx.doi.org/10.1016/j.ijepes.2014.06.038
0142-0615/

Hypotheses and market framework

Distributed generation

An extensive list of modern DG and storage units is offered in [21,22]. One should note that most of the DG technologies offer fast cold start/reserve (small start times) and that they are fully dispatchable [22].

Virtual power plant

A VPP may consist of various DGs connected at distant locations in the distribution network or under a single feeder. It may also include loads, non-interruptible and/or interruptible; the latter subject to DSM. All distributed resources of the VPP are supposed to be centrally controlled.

Market framework

A joint market of energy and ancillary services is assumed; the Independent System Operator runs the day-ahead market [18]. Each participant submits bids of price ρ and active power P (in kW). The VPP profit is:

$$\begin{aligned} \textit{Dispatch Profit} = & -\rho_{E,t+1}E_{t+1} + \rho_{R,t+1}R_{t+1} + \rho_{L,t+1}\textit{Load}_{t+1} \\ & - \sum_{i \in S_{DG}} [C_{DG,i,t+1}(P_{DG,i,t+1} + R_{DG,i,t+1})I_{i,t+1} + SC_{DG,i,t+1}J_{i,t+1}] \\ & - \sum_{i \in S_{\text{int}}} C_{\text{int},i,t+1}R_{\text{int},i,t+1} - \sum_{i \in S_{str}} C_{str,i,t+1}P_{str,i,t+1} \end{aligned} \quad (1)$$

where $t+1$ denotes the hour-ahead scheduling horizon, ρ_E, ρ_R and ρ_L are the prices of energy, spinning reserve and retail energy, respectively, E is the energy sold/bought by the VPP to the market, R is the sum of reserves of the DGs of the VPP, *Load* is the load served within the VPP, C represents the cost function of each DG, interruptible load (subscript *int*) or storage device (subscript *str*), SC is the start-up cost of each DG, I and J are binary variables denoting the operation and the start-up of each DG, respectively. The profit is calculated as the sum of the revenues of energy ($E_{t+1} < 0$) and reserves sold to the market by the VPP and the energy supplied to the load within the VPP, minus the sum of the operating costs of the DG units, of the DSM and of any start-up costs incurred during the hour. Further details on (1) can be found in [18].

Data requirements

The following data is required:

a. The hourly schedule of the VPP (e.g. [18]), an hourly load forecast or estimation (e.g. [23] or [24]),
b. The data required by (1) and the transfer function of all DG units and storage devices.

A basic communication infrastructure is required for the transmission of commands and data [25].

Specifics of the problem of FPC provision by VPPs

As previously mentioned, a VPP can cover an unexpected loss of power by dispatching accordingly its available "hot" and "cold" reserves. This procedure cannot be performed in a simple and unique way because:

– the DGs have different cost functions, start times, available margins and varying costs of fuels/feedstock, thus implying a large number of possible combinations changing over time,
– the loads of the VPP (representing also part of the flexible load) may deviate from the expected, due to forecasting inaccuracies,
– the load of the rest of the PS cannot be supposed to be observed by the VPP operator but only estimated,
– there exist thermal limits of lines and loading limits of the distribution transformers shared also by DGs and
– the "hot" reserve may be insufficient and the "cold" reserve may offer a cheaper dispatch of the power loss.

The above points describe a probabilistic constrained non-linear optimization problem. Its analytical approach will account for a theoretically infinite number of possible solutions. Moreover, the stochastic nature of certain variables of the loss dispatch (i.e. RES-based DG units of the VPP) implies that a specific optimal dispatch may be impossible to realize, due to available power out and below the confidence intervals initially assumed. In this paper, a data-mining application is proposed; Decision Trees (DT) will be used as the tool with the most positive and suitable characteristics [26] for this problem.

Decision trees

A DT is a tree structure which extracts rules from a Learning Set (LS) of pre-classified data [27]. In PS studies, DTs often process data of binary sorting, i.e. True/False, Safe/Unsafe, etc. Each internal node splits the available subset in two parts (children nodes) on a single attribute. If the subset of a child node is pure enough with respect to one of the classes, it is declared terminal, otherwise it is further split. Conventionally, the left child complies with the split criterion of the parent node, e.g. in the DT of Fig. 1, node 2 includes the subset of the LS for which A1 $\geqslant$ 8.2.

A terminal node can be either a leaf (acceptable purity and not split any further) or a dead-end (not acceptable purity and not split any further). For each leaf, the path leading to the root can be written in the form of if-then-else statements, which can be used as rules; e.g. the rules given from the DT of Fig. 1 are:

Rule (i): if (A1 $\geqslant$ 8.2) *then* FALSE and *Rule (ii): if* (A1 < 8.2) *and* (A7 = FALSE) *then* TRUE

The following characteristics have to be kept in mind:

a. The stop criteria define if the rules of the DT can be "generalized" or if the DT has been over-fitted to the LS. The split selection methodology accounts for whether "enough" rules were produced by the DT [29].
b. The DT may not perform satisfactorily on unseen cases (generalization ability) [30].
c. When for a single LS, there exist multiple DTs describing the knowledge problem, then the DT with the highest generalization ability should be selected [30]. This may also apply to the case when several similar LSs can be used to build a DT for the same knowledge problem.

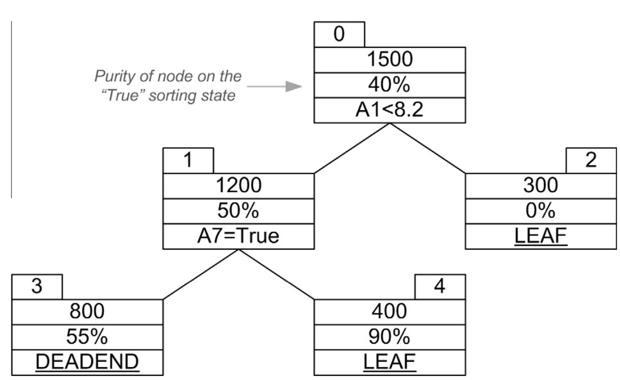

Fig. 1. Example of a univariate, binary DT.