Study Committee D2

Information Systems and Telecommunication

Paper 10618_2022

MACHINE LEARNING APPROACH FOR POWER FLOW CONTROL IN CONGESTED GRIDS WITH LARGE SHARE OF VARIABLE ENERGY RESOURCES

Evgeny TSYDENOV, Anton PROKHOROV

National Research Tomsk Polytechnic University

Motivation

In addition to recent advances in variable energy resources (VER) forecasting and online capacity equipment rating, flexible real-time control of power flows must be implemented to ensure efficient utilization of VER over the existing grids.

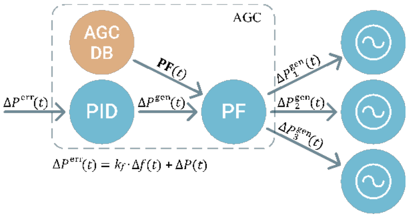

Figure 1: Functional diagram of AGC (AGC DB — database of AGC, PID — proportional–integral–derivative controller, PF — participation factors)

In transmission grids, this task is handled by automatic generation control (AGC) systems which face additional challenges caused by the trend of VER involvement in the secondary control. Thus, existing AGC systems need to be enhanced to keep up with the ongoing industry changes.

Approach

The paper proposes an approach for online computation of plant participation factors (PF) that advances power flow control selectivity and flexibility.

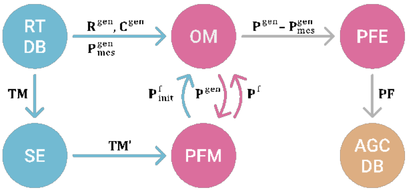

Figure 2: The algorithm for online computation of participation factors (RTDB — real-time database, OM — optimization model, PFE — estimator of participation factors, SE — state estimator, PFM — power flow model, AGC DB — database of AGC)

To fit the algorithm to the particular control task, it is necessary to set an objective function which generalized form looks as follows:

$$f(\mathbf{P}^{gen}) = \sum_i w_i \cdot f_i(\mathbf{P}^{gen})$$

The function is organized as a weighted sum of optimization criteria $f_i(\mathbf{P}^{gen})$, which are defined according to the control task and consider economic (e.g., $\mathbf{C}^{gen}$), technological (e.g., $\mathbf{R}^{gen}$), or state parameters (e.g., $\mathbf{P}^{f}$).

The optimization criteria and their weighting coefficients w_i can be adjusted according to the specifics of power system characteristics and utility's experience. Besides, there are several conditions that should be used as constraints:

$$U_n^{min} < U_n(\mathbf{P}^{gen}) < U_n^{max}, \qquad n = 1, 2, \dots, m,$$

$$\frac{dP_i^{gen}}{d\delta_i} > 0, \qquad i = 1, 2, \dots, k,$$

$$\mathbf{P}^{gen}_{init} - \mathbf{R}^{gen}_{down} \le \mathbf{P}^{gen} \le \mathbf{P}^{gen}_{init} + \mathbf{R}^{gen}_{up}$$

To meet the performance requirements imposed by VER, the paper proposes to replace the conventional Newton-Raphson (N-R) power flow solver with machine learning (ML) techniques.

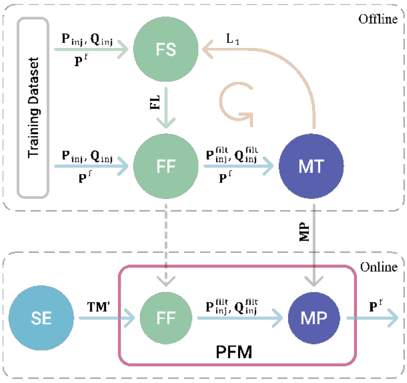

Figure 3: Proposed pipeline for power flow calculation by ML model (FS — feature selection component, FF — feature filter, MT — model training tool, MP — ML-based solver, SE and PFM — state estimator and power flow model as in Figure 2)

Contribution

The main contributions of this paper are the following:

- the online approach for optimal computation of PFs was developed to boost selectivity and flexibility of existing AGC systems;
- the multi-task objective function was proposed to estimate PFs, and its feasibility was proved for conventional and advanced power flow control tasks;
- the densely connected NN was built as a power flow model of real 60 GW interconnection and adapted to the considered AGC tasks that made power flow calculations faster than with the Newton-Raphson method;
- Lasso regression was suggested and implemented as a feature selection tool to boost the accuracy and decrease inference time of the ML-based power flow model.

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Experiment Setup

The power flow model representing one of control areas of the Russian power system with 60 GW of thermal-hydro generation capacity is used as a testbed. The model consists of 464 nodes and 742 branches.

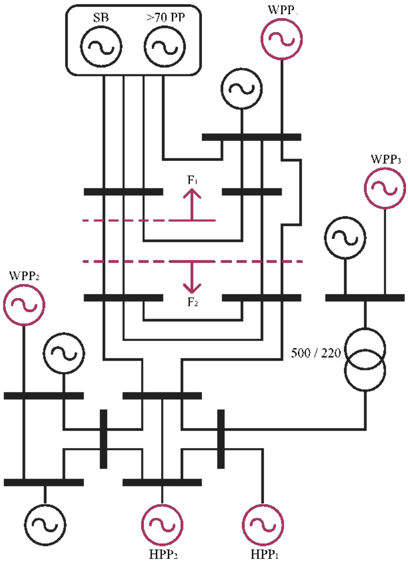

Figure 4: Simplified structure of the test system

Some part of the capacity of existing generating nodes was substituted with wind power plants (WPP_1, WPP_2, and WPP_3) having respectively 600, 600, and 300 MW of installed capacity and assigned for providing regulating reserves.

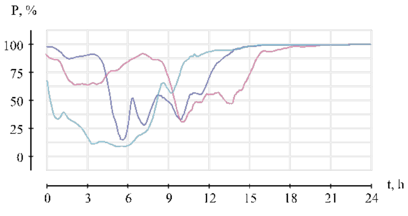

Figure 5: Change of WPP outputs within the operating day

Since hydropower plant (HPP) reserves are mostly defined by water use rules or climate conditions, they change insignificantly within the operating day. Thus, up and down reserves for each HPP were assumed to be 50 MW in all experiments. In addition, it was assumed that WPPs can use 10% of their available active power output to ramp down under the AGC commands.

Conventional Power Flow Control

The task of PFs estimation for power flow control over flowgate F_1 is considered here. In the control area, the AGC system commands two hydropower plants (HPP_1 and HPP_2) and three wind power plants (WPP_1, WPP_2, and WPP_3). The Newton-Raphson method was applied for power flows calculation as a standard approach used in the industry.

To fit the algorithm to this conventional control task, the following objective function was formulated:

$$f(\mathbf{P}^{\mathrm{gen}}) = w_1 \cdot f_1(\mathbf{P}^{\mathrm{gen}}) + w_2 \cdot f_2(\mathbf{P}^{\mathrm{gen}})$$

$$f_1(\mathbf{P}^{\mathrm{gen}}) = \left|P^{\mathrm{F1}} - (P^{\mathrm{F1}}_{\mathrm{init}} + \Delta P^{\mathrm{F1}}_{\mathrm{aim}})\right|$$

$$f_2(\mathbf{P}^{\mathrm{gen}}) = \left\|\mathbf{k}_{\mathrm{R}} \circ (\mathbf{P}^{\mathrm{gen}} - \mathbf{P}^{\mathrm{gen}}_{\mathrm{mes}}).\wedge n\right\|_1$$

The average number of power flow computations necessary to find PF values in this case is 17541. As a result, the time of PF estimation is about 251.04 s.

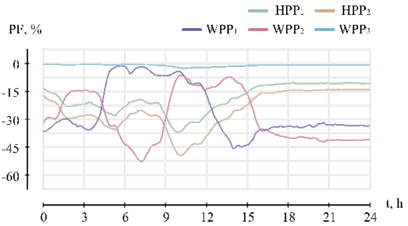

Figure 6: PF values of HPPs and WPPs commanded by AGC

Power Flow Control Considering Adjacent Lines Overload

To enhance the AGC system selectivity, it is worth to account power flows over adjacent branches with limited transfer capability that may help to avoid their overloads during the control process. To release this type of control in the considered test system, it is proposed to add a third component $f_3(\mathbf{P}^{\mathrm{gen}})$ with a weighting coefficient w_3 to the objective function above:

$$f(\mathbf{P}^{\mathrm{gen}}) = \sum_{i=1}^{3} w_i \cdot f_i(\mathbf{P}^{\mathrm{gen}})$$

$$f_1(\mathbf{P}^{\mathrm{gen}}) = \left|P^{\mathrm{F1}} - (P^{\mathrm{F1}}_{\mathrm{init}} + \Delta P^{\mathrm{F1}}_{\mathrm{aim}})\right|$$

$$f_2(\mathbf{P}^{\mathrm{gen}}) = \left\|\mathbf{k}_{\mathrm{R}} \circ (\mathbf{P}^{\mathrm{gen}} - \mathbf{P}^{\mathrm{gen}}_{\mathrm{mes}}).\wedge n\right\|_1$$

$$f_3(\mathbf{P}^{\mathrm{gen}}) = \left|P^{\mathrm{F2}} - P^{\mathrm{F2}}_{\mathrm{init}}\right|$$

The experiment shows the results of PF calculation with three values of w_3 — w_{3A}, w_{3B}, w_{3C} such as:

$$0 \leq w_{3A} < w_{3B} < w_{3C}$$

The average number of power flow computations necessary to calculate optimal PF values in the considered experiments is 18484. Thus, PF estimation time is about 253.33 s.

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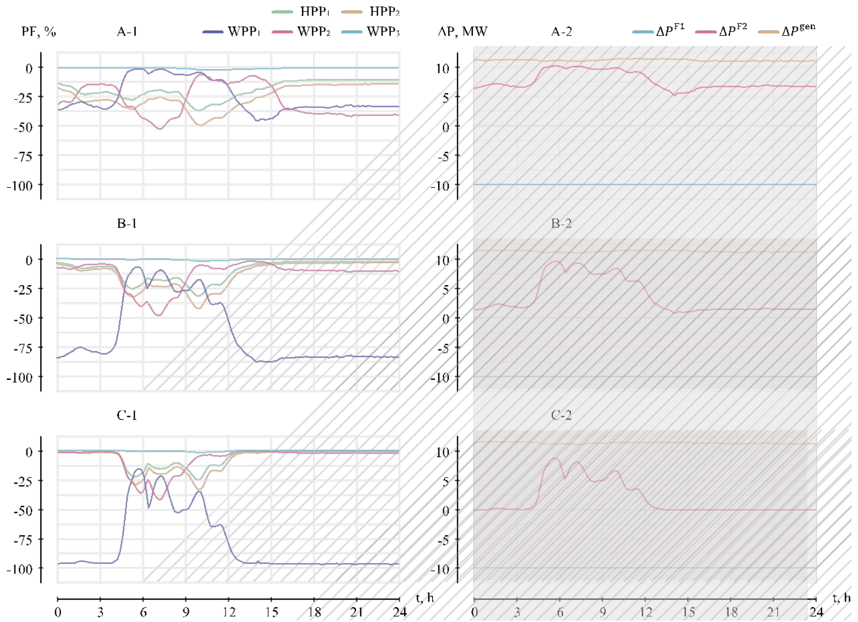

Figure 7: PF values of power plants commanded by the AGC system with three different values of w_s (A — 0, B — w_{ag}, C — w_{ac})

Use of Machine Learning Based Power Flow Estimator

To speed up power flow calculations and hence the PF estimation process, the paper proposes to replace the conventional N-R power flow method with ML model. This section demonstrates an experiment of PF estimation using ML-based power flow solver for the same task of power flow control over flowgate F_1 as considered earlier.

The densely connected neural network (NN) was chosen as a power flow estimator. The brief information of the built model:

- Predicted value is a power flow over the flowgate F_1.
- Feature vector is a set of nodal injections filtered with the Lasso regression algorithm.
- Training dataset contained 500 000 power flow cases (60% — training set, 20% — validation set, and 20% — test set).
- Hyperparameters: two hidden layers, Leaky ReLU activation function with slope 0.2, Huber loss function, Adam optimizer.

The mean absolute error of the trained model predictions on the test dataset is less than 0.03 MW.

Table I: Performance comparison

Exp. №	Power flow solver	Number of iterations	Time, s
I	N-R	17541	251.04
II	N-R	18484	253.33
III	NN	24206	30.18

The time of power flow computation with the proposed NN model is 1.1 ms that makes it 11 times faster than in case of N-R algorithm usage.

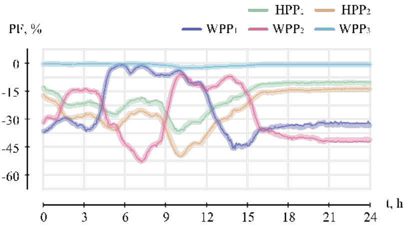

Figure 8: PF values of HPPs and WPPs commanded by AGC (use of NN model for power flow computation — solid lines, use of the N-R algorithm — blurred lines)