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Clustering methods for the efficient voltage regulation in smart grids

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Abstract
In this paper, clustering methods are presented to enhance the stability of automatic voltage regulators using the efficient adjustment of their respective gains. The results show that implementations of some of the clustering algorithms provide better reliability and stability for the feedback-based voltage regulators as compared to the other methods, namely, a model predictive controller (MPC), a gaussian mixture model (GMM), a self-organizing mapping (SOM) and hierarchical clustering (HC) methods. Specifically, the K-Means clustering approach (KM) provided superior stability but a slower rise time of the output voltage of the voltage regulators as compared to the other methods. Furthermore, coordination of the clustering methods is tested for a 10 machine, 39 bus power grid system. The results show that the clustering approach could be applied to improve the efficiency of voltage regulation methods in smart grids and related cyber-physical systems.

1 | INTRODUCTION

Automatic voltage regulators (AVRs) are employed to stabilize the terminal voltages of medium, high, or extra high voltage power grids. AVR systems constitute an amplifier, an exciter, a generator, and a sensor-based feedback system. A system diagram of an AVR is shown in Figure 1, where the AVR is connected to a given power grid system. In the Laplace domain, the transfer function $G(s)$ of the PID controller is given in (1), where the proportional, the integral, and the derivative gains are represented by $K_p$, $K_i$, and $K_d$, respectively [1].

$$G(s) = K_p + \frac{K_i}{s} + K_ds$$

(1)

A major focus of modern literature is the efficiency optimization methods for AVR systems based on proportional integral derivative (PID) controllers. Related literature focuses on optimizing PID parameters in AVR systems. This paper presents clustering and coordination methods based on the voltage regulation variables such as the terminal voltage, the amplifier voltage, the exciter voltage, the generator voltage and the power grid variables such as the bus voltage to adjust the output voltage of the AVR system. The clustering method is proposed to identify related terminal voltage values and compute the gains for the AVR system as shown in Figure 2.

The main contributions of this paper are fourfold. First, a system equation describing the implementation of unsupervised learning algorithms for automatic voltage regulation systems is presented. Second, the controller gains of a selected four unsupervised learning methods are computed. Third, the implementations of the four methods are presented and compared with other types of conventional control methods. Finally, a recommendation on how to select a good unsupervised learning method for automatic voltage regulation is presented considering a smart grid operational environment.

2 | LITERATURE ON AUTOMATIC VOLTAGE REGULATION

Voltage regulator designs have been improved significantly for various applications in the past decade. Hardware controller designs and software control algorithms have been applied to optimize the voltage regulator performance [2] and new circuit schematics have been presented to improve the performance of various types of regulators. For medium-voltage regulation systems, a genetic algorithm (GA) was used to obtain optimal
Moreover, a hybrid control system for an AVR was proposed using a fuzzy sliding mode control and a neural network supervised learning procedure in [13]. The Taguchi combined genetic algorithm (TCGA) was used to determine optimal values for PID controller parameters, where optimum values for the two influential design variables were found using a multiobjective GA. The TCGA produced a settling time of 0.52 s while PSO and GA produced settling times of 0.81 and 0.86 s, respectively.

Furthermore, the maximum per cent overshoot produced by the TCGA was just 0.36% of that produced by the PSO [1]. A fuzzy logic controller-based AVR design was presented in [14]. The fuzzy controller showed a four-second settling time, which was faster than all the compared PID controller variants, also proved to be much better than the other controllers in terms of overshoot, albeit a slower response. In addition, a grasshopper optimization algorithm (GOA) was recently presented for this purpose. The results showed that the algorithm outperforms the previously proposed control methods in maximum overshoot, settling time, rise time, and peak time [15].

For high voltage systems, an algorithm was presented to compute the optimal allocation and configuration of voltage regulators and capacitor banks in power distribution systems in [16]. The algorithm first determined the power flow using a current sum method and then used a genetic algorithm for the allocation and configuration of equipment. An adaptation function was used to evaluate the fitness of each member of the GA based on a weighted criterion. SCADA and control algorithms were used in integrated modules to control the voltage levels inside the regulation area [17].

The need for smart voltage regulators was also highlighted by researchers to the auto-correct voltage on lines [18]. A new operating mode for voltage regulators in a smart grid system was presented by tapping between different control operations to handle reverse power flow in [19]. Parallel computing was used to reduce computational time and improve optimization parameters of voltage regulators in [20]. Big data analytics of smart meter data showed a prediction accuracy of 84.02% with a minimum prediction accuracy of 64.71% in [21]. Adaptive hierarchical voltage control methods for distributed voltage control were presented in [22, 23]. At a local level, the voltage regulator hardware processed load data, source voltage data, and tap position adjustment data to determine the best set of adjustments to the equipment in any operating condition. A fuzzy controller then sets the optimal parameters and sends the configuration to the centralized controller for hierarchical processing. The central controller took each voltage regulator parameter into account once it set its settings.

Comparisons of the recent developments of AVR systems in the medium, high, and ultra-high voltage ranges are presented in Table 1. The voltage and current efficiency, performance, and stability comparisons are shown in radar charts in Figure 3. AVR at the medium and high voltage levels could process, define, and adjust terminal voltages. However, coordination of multiple AVRs requires clustering methods that are not yet fully addressed in the literature. Such an approach would require learning and coordination with other voltage regulators.
in the network. This is addressed in this work using coordination approaches for the voltage clusters.

3 | CLUSTERING METHODS FOR VOLTAGE REGULATION

The implementation of clustering methods for classification, regression and clustering of voltage regulator data is a new research area [24, 25, 26]. Rather than a supervised approach, this paper focuses on the unsupervised clustering methods, which do not require any labelling or training resources. The methods include a k-means clustering-based controller (KM), a hierarchical clustering controller (HIE), a Gaussian mixture model-based controller (GMM) and a self-organizing mapping-based controller (SOM). The implementations are compared to a model predictive controller (MPC), a fuzzy logic controller (Fuzzy), and a proportional integral derivative controller (PID). The KM divided data into five categories based on model data generated by the user and updated the proportional gain of the controller according to the terminal voltage of the regulator. The MPC is added in parallel with the PID controller and gets tuned. The fuzzy system replaced the PID and MPC blocks in the AVR system, and the voltage profiles were obtained. The fuzzy logic controller used five triangular membership functions to classify the terminal voltages of the regulator. The transfer functions for each unsupervised machine learning method are calculated from the step response of the implemented system. The corresponding proportional, integral, and derivative gains were calculated from the time delay, the overshoot, the settling time, and the steady-state error of the step response using the Ziegler Nichols method as given in (2) to (9) and Table 2. The time delay is represented by \(L\), the time constant is \(T\), and the gain is \(K\). As an example, the proposed Gaussian Mixture Model for AVR coordination is given in Figure 4.

\[
G_{PID}(s) = K_p \left(1 + \frac{1}{T_i} + T_d s\right) \tag{2}
\]

\[
OS = \frac{V_{PEAK} - V_{REF}}{V_{REF}} \times 100\% \tag{3}
\]

\[
K_{UML,GMM} = 0.291 + \frac{0.182}{s} + 0.728s \tag{4}
\]

\[
K_{UML,SOM} = 0.282 + \frac{0.176}{s} + 0.705s \tag{5}
\]

\[
K_{UML,HIE} = 0.132 + \frac{0.083}{s} + 0.33s \tag{6}
\]

\[
K_{Overall} = \frac{1}{1 + \left(\frac{K_{UML}}{0.1(1+0.4+1)(1+1)}\right)} (K_{UML}) \tag{7}
\]

\[
S_f = \frac{50s + 5000}{2s^2 + 221s^3 + 2775s^2 + 7550s + 1000} \tag{8}
\]

\[
S_f,GMM = \frac{1000s (s+1000)}{40s^2 + 4540s^3 + 56228s^2 + 224091s^2 + 229828s + 18200} \tag{9}
\]
4 | RESULTS AND DISCUSSION

The terminal voltages of the individual AVR systems with a fixed reference voltage are shown in Figure 5. The terminal voltages of the individual AVR systems with a dynamic reference voltage are shown in Figure 6. Rise time is the time required for the voltage to rise from 10% to 90% of its steady value. Settling time is the time taken for the voltage to converge within 5% of the reference voltage $V_{REF}$. The overshoot is calculated from the peak voltage value ($V_{PEAK}$) and the settling value. The error, amplifier, and exciter voltage comparisons are shown in Figures 7, 8, and 9. Moreover, using a dynamic three pulsed input as a reference voltage, the error, amplifier, and exciter voltage comparisons are shown in Figures 10, 11, and 12.

The strengths and weaknesses of the different controllers for individual AVR systems are evaluated in this paper. The MPC yielded the fastest response time of 0.182 s. Furthermore, the overshoot produced by the MPC is more stable than both the...
PID and Fuzzy logic by 0.2% and 3%, respectively. However, the PID has a faster settling time than the MPC by 1.293 s. The K-means controlled AVR system is far superior to the other smart AVR systems in terms of stability. The maximum per cent overshoot is only 1.2% and therefore the settling time is 0 seconds since the peak value is within 5% of the reference voltage. The downside of the K-means controller is a slow rise time of...
The simulations of AVR systems with dynamic reference voltages provide evidence that the rise time of the K-means algorithm-based learning system can compete with the rise time of the MPC controller.

0.42 s. This rise time is 0.238 s slower than the rise time of the MPC controller.
FIGURE 20  Rotor speeds using no coordination

FIGURE 21  Machine angles using clustered coordination

FIGURE 22  Rotor speeds using clustered coordination

times of the other controllers. The average rise time of the K-means controller over 3 pulse waves is 0.209 s. This rise time is only 0.005 s slower than that of the MPC and faster than both the PID and Fuzzy Logic controllers by 0.022 and 0.103 s, respectively. The settling time of the K-means controller is the fastest of the four controllers with an average of 0.221 s. The K-means controller continues to perform the best in terms of stability with an average overshoot of 6.33%. These results illustrate a K-means algorithm-based learning system provides superior stability in automatic voltage regulator-based systems. Furthermore, integrating multiple controllers in AVR-based systems could provide the most efficient energy conversion operation.

Coordination of the clustering methods was also considered using 10 AVR systems interfacing 10 generators in the IEEE 39-bus system. The system is commonly called the New England...
The variables that are used for coordinating the operation of the AVR systems include the rotor angles, the rotor speeds, the stator voltages, the field excitation, the machine angles, and the machine frequencies. Results of the implementation indicate better stability of each of the variables due to the coordinated control of the AVR systems. The derivatives of the rotor angles using no coordination and GMM based coordination are shown in Figures 13 and 14. The derivatives of the rotor speeds using no coordination and GMM based coordination are shown in Figures 15 and 16. The field excitation using no coordination and GMM based coordination are shown in Figures 17 and 18. The machine angles and frequencies using no coordination and GMM based coordination are shown in Figures 19 and 21. The rotor speeds using no coordination and GMM based coordination are shown in Figures 20 and 22. The
FIGURE 26 System real power using clustered coordination

FIGURE 27 Stator voltages using no coordination

FIGURE 28 Stator voltages using clustered coordination

FIGURE 29 Turbine real power using no coordination

FIGURE 30 Turbine real power using clustered coordination

FIGURE 31 Turbine reactive power using no coordination

FIGURE 32 Turbine reactive power using clustered coordination

System voltages and powers using no coordination and GMM based coordination as shown in Figures 23 and 25. The system’s real power using no coordination and GMM based coordination are shown in Figure 26. The stator voltages using no coordination and GMM based coordination are shown in Figures 27 and 28. The turbine real and reactive power values using no coordination and GMM based coordination are shown in Figures 29, 30, 31, and 32, respectively. In real-world systems, the data from the clustering methods implemented in distributed AVRIs could be communicated via the internet for better stability and efficiency of generator parameters such as rotor angles, speeds, field excitation voltages, stator voltages, and real and reactive powers of the machines.

5 | DISCUSSION

The novelty and contribution of this work includes the application of clustering methods for automatic voltage regulation for smart grids application. The approach is scalable to large-scale
smart grid systems having more than thousands of voltage terminals interfaced with automatic voltage regulators.

6 | CONCLUSION AND FUTURE WORK

A voltage regulator is a circuit that maintains the output voltage at a stable potential difference despite input voltage changes, load differences, and operational irregularities. The paper presented clustering methods for the efficiency of automatic voltage regulation. In the actual operation, different factors affect how fast a voltage regulator returns to steady-state conditions after changes in load conditions, and therefore, coordination methods are necessary to ensure the stability of the overall system. In the future, the clustering methods could be applied to other components of a power grid to result in further improvements in the efficiency and stability of the interconnected system. Although clustering methods have been presented in this work, other types of methods could also be applied to AVR systems. Those implementations would be considered as future work.

Nomenclature

\[ G_{PID}(s) \] PID gain
\[ K_{Overall} \] Overall gain
\[ K_{UML,GMM} \] Gain of GMM

\[ K_{UML,HIE} \] Gain of HIE
\[ K_{UML,SOM} \] Gain of SOM
\[ V_{REF,AK} \] Peak voltage
\[ V_{REF} \] Reference voltage
\[ AP SO \] Adaptive PSO
\[ AVR \] Automatic voltage regulator
\[ G(s) \] Transfer function of the PID controller
\[ GA \] Genetic algorithm
\[ GMM \] Gaussian mixture model
\[ GOA \] Grasshopper optimization algorithm
\[ HC \] Hierarchical clustering
\[ KM \] K-means clustering
\[ K_p, K_i, K_d \] Proportional, integral, derivative (PID) gains
\[ MPC \] Model predictive controller
\[ PSO \] Particle swarm optimization
\[ RMS \] Root-mean square
\[ SCADA \] Supervisory control and data acquisition
\[ SOM \] Self-organizing mapping
\[ TCGA \] Taguchi Combined Genetic Algorithm
\[ UML \] Unsupervised machine learning
\[ OS \] Overshoot
\[ Sys \] Transfer function of the system
\[ SysGMM \] Overall transfer function of the GMM

CONFLICT OF INTEREST

There is no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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