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Clustering methods for the efficient voltage regulation in smart grids

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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].

$$G(s) = K_p + \frac{K_i}{s} + K_d s \tag{1}$$

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

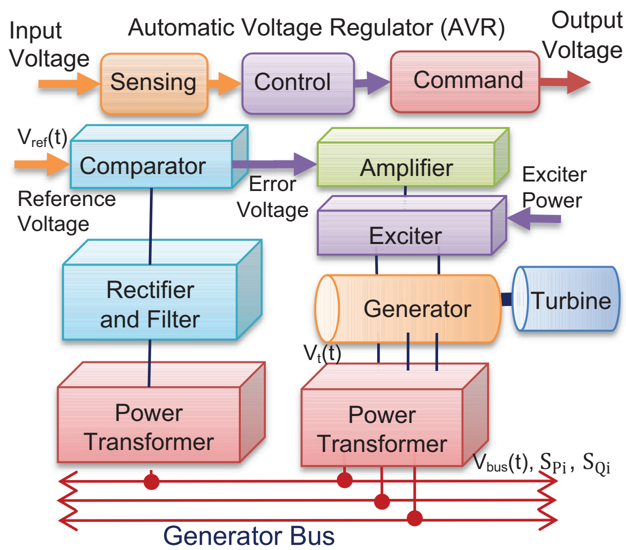

FIGURE 1 A system containing an AVR

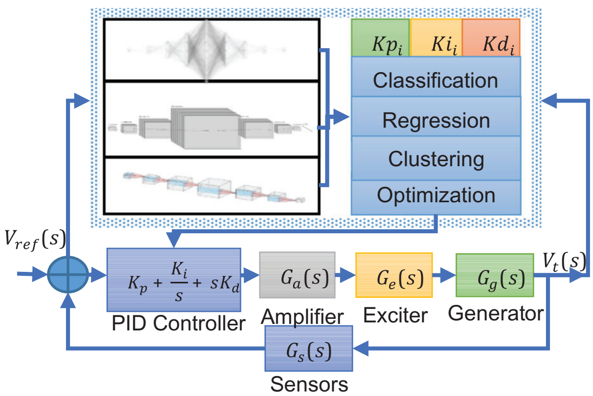

FIGURE 2 Clustering methods for AVR coordination

PID parameters using a Sugeno fuzzy logic model in less than one second for real-time operations [3]. A differential evolution algorithm was used in [2]. A self-tuning PID controller using a recursive least-square-based linearization and feedback was implemented to find the control system parameters with 10% error on the root mean squared (RMS) voltage in [4]. A particle swarm optimization (PSO) algorithm was used to generate optimal three parameters for the PID controller [5] and a simplified PSO algorithm and an adaptive PSO (APSO) algorithm were proposed for optimizing PID settings in [6]. The simplified algorithm allowed for easy tuning of behavioural parameters, and resulted in better convergence and accuracy, with a settling time of 0.564 s and a peak amplitude of 1.01 V [6]. A heuristic method called Ziegler-Nichols was used to tune the parameters of the PID controller in [7]. With a rise time of over 0.3 s, this method was not as efficient as a PSO or a GA. However, it simplified the testing process and was compatible with tuning methods. Recently, learning-based approaches are being implemented, including spectral clustering [8], reinforcement learning [9] and deep learning [10–12].

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 multi-objective 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 tap changing 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 hierarchal 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 hierarchal 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

TABLE 1 Efficiency comparison of AVR system controllers

Comparison variable	Genetic algorithm and fuzzy logic [3]	Adaptive particle swarm optimization [6]	Genetic algorithm and Taguchi fuzzy logic [1]	Fuzzy logic controller [15]	Grasshopper optimization [16]
Year	2009	2013	2013	2017	2018
Controller	PID	PID	PID	Fuzzy logic	PID
Algorithm	GA, Sugeno fuzzy logic	APSO	GA, Taguchi fuzzy logic	Fuzzy logic	GOA
Overshoot	0.084%	1%	0.006%	0%	20.50%
Rise time	0.765–1.33 s	0.346 s	0.63 s	–	0.13 s
Settling time	0.765–1.80 s	0.564 s	0.52 s	4s	0.971 s

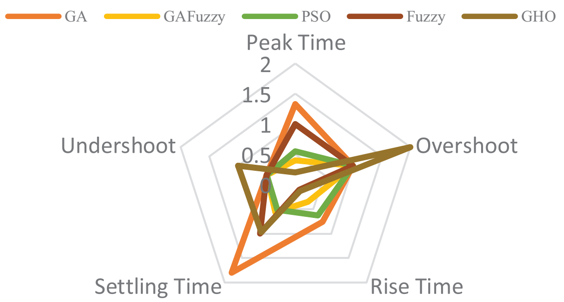

FIGURE 3 Stability comparison of smart AVR controllers

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

TABLE 2 Ziegler Nichols method of calculating gains

Method	K_p	T_i	T_d
P	T/L	∞	0
PI	0.9T/L	L/0.3	0
PID	1.2T/L	2L	0.5L

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.

$$G_{PID}(s) = K_p\left(1 + \frac{1}{T_I s} + T_D s\right) \tag{2}$$

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

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

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

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

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

$$Sys = \frac{50s + 5000}{2s^4 + 227s^3 + 2775s^2 + 7550s + 1000} \tag{8}$$

$$SysGMM = \frac{1000s(s + 1000)}{40s^5 + 4540s^4 + 56228s^3 + 224091s^2 + 229282s + 18200} \tag{9}$$

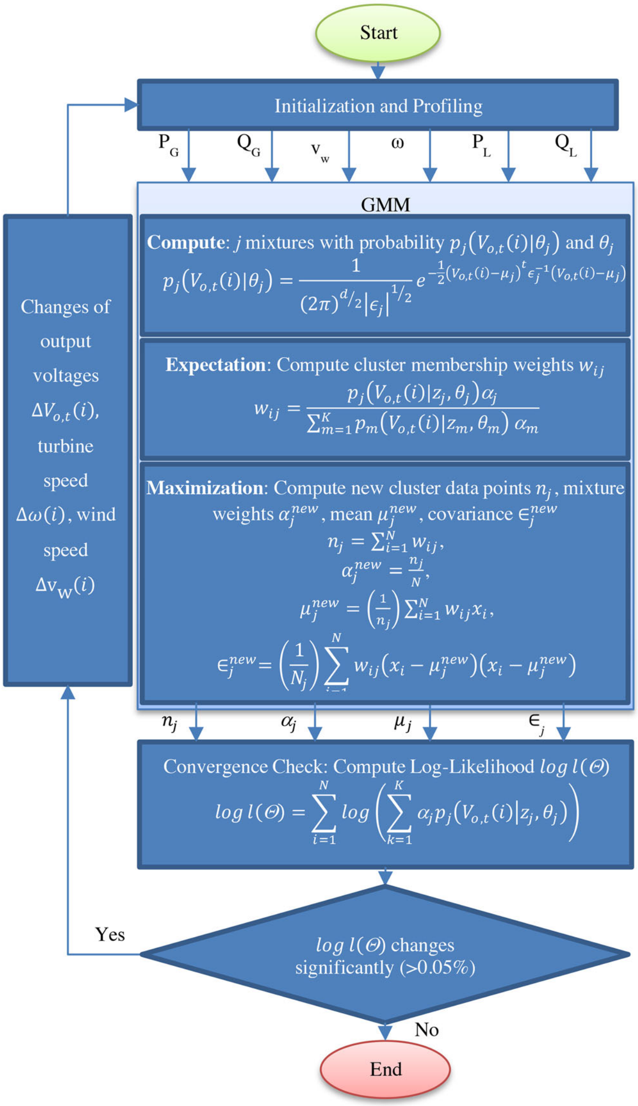

FIGURE 4 Gaussian mixture model

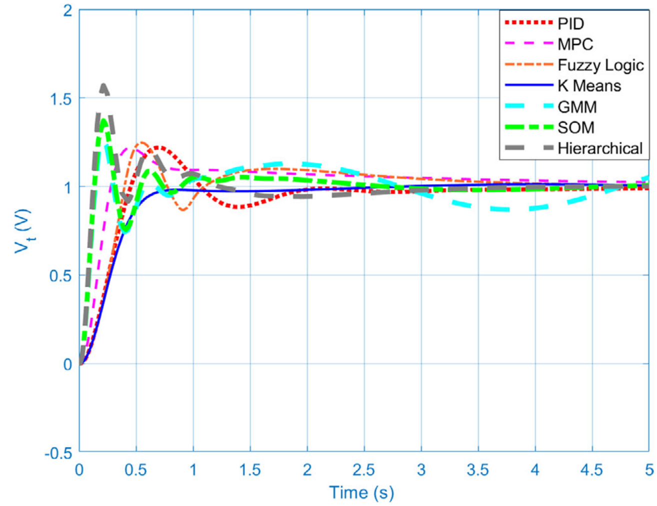

FIGURE 5 Terminal voltages stability comparison

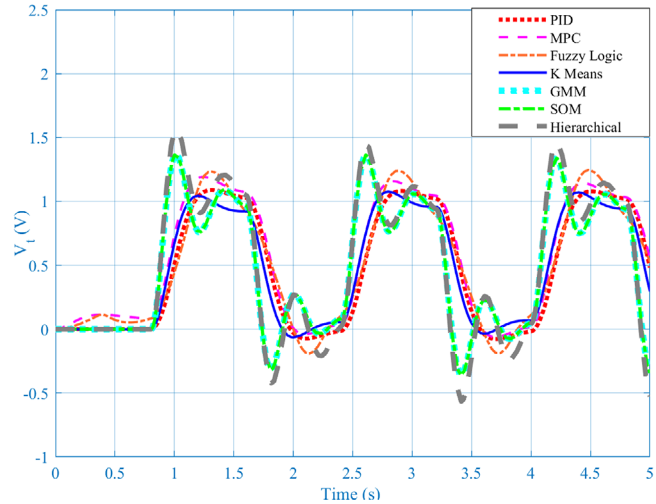

FIGURE 6 Terminal voltages using dynamic reference voltages

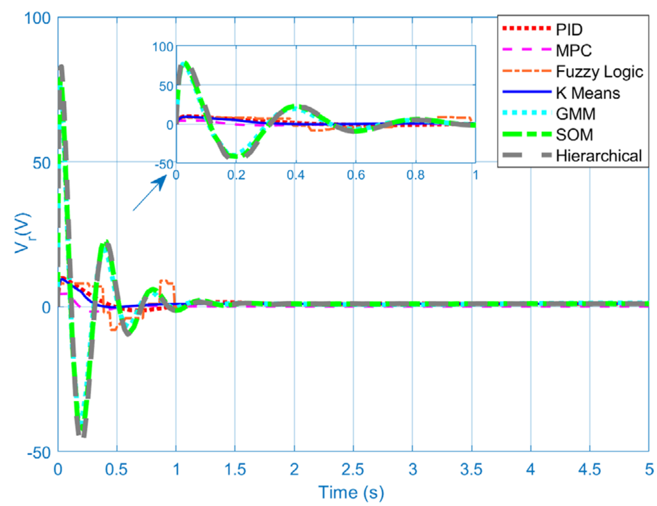

FIGURE 7 Error voltages comparison

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

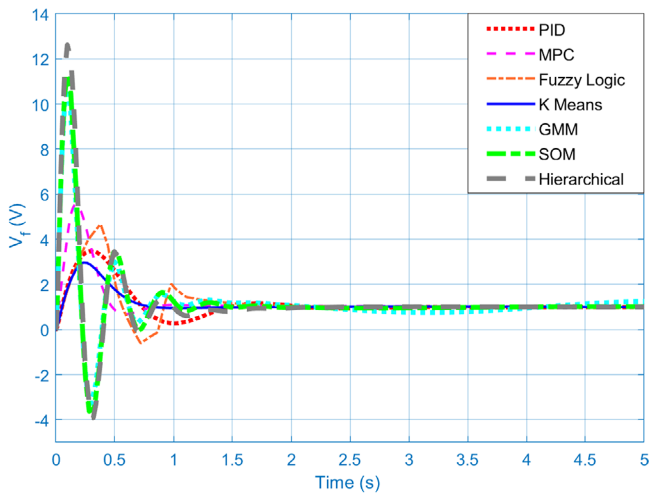

FIGURE 8 Amplifier voltages comparison

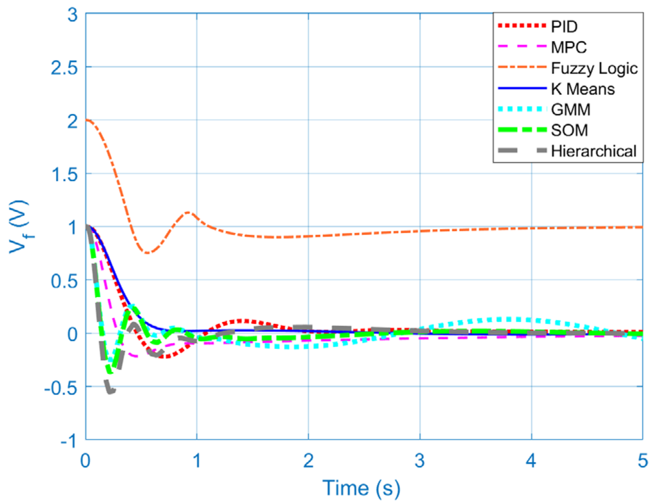

FIGURE 9 Exciter voltages comparison

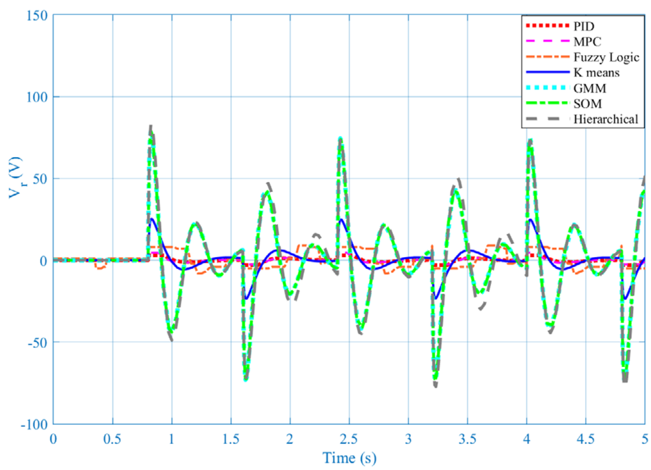

FIGURE 10 Error voltages using dynamic reference voltages

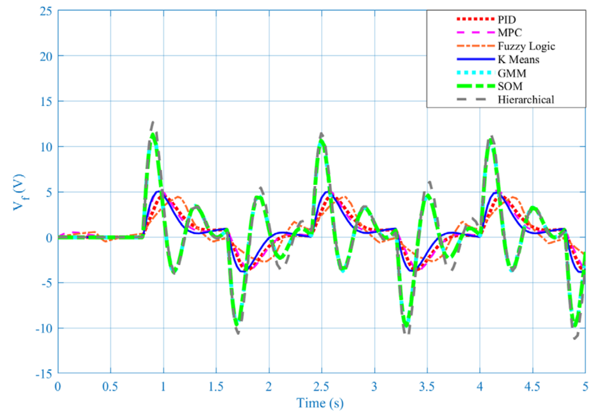

FIGURE 11 Amplifier voltages using dynamic reference voltages

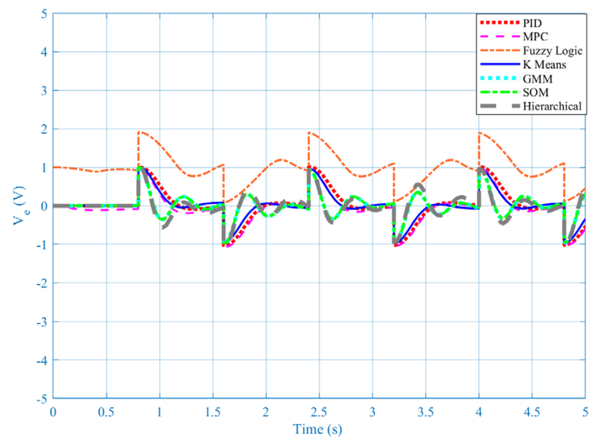

FIGURE 12 Exciter voltages using dynamic reference voltages

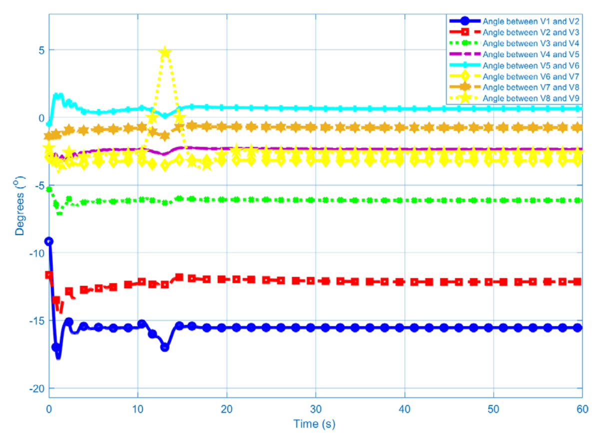

FIGURE 13 Derivative of rotor angles using no coordination

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

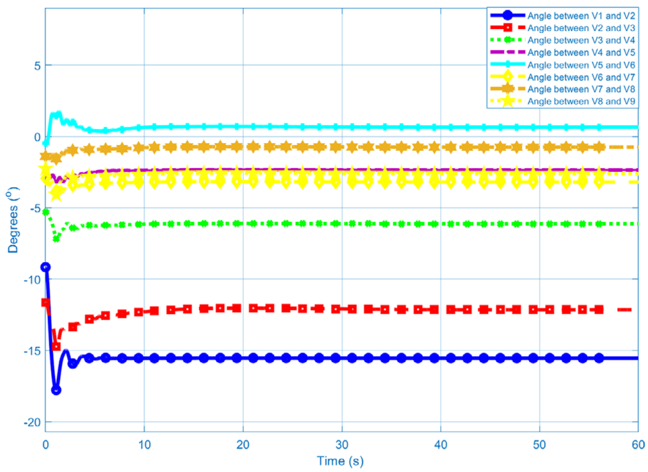

FIGURE 14 Derivative of rotor angles using GMM based coordination

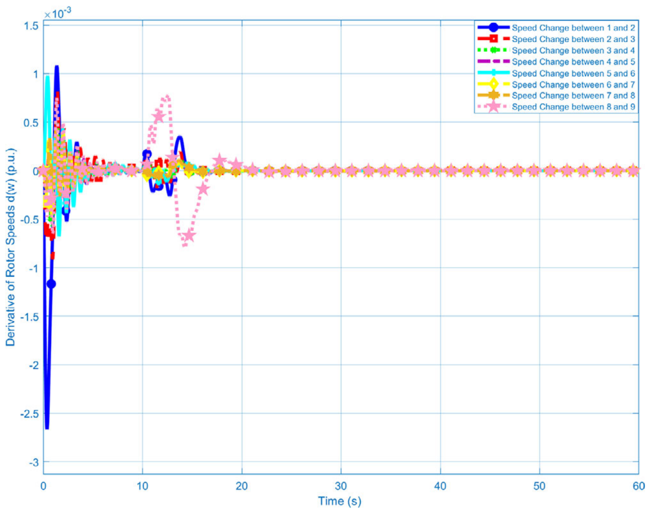

FIGURE 15 Derivative of rotor speeds using no coordination

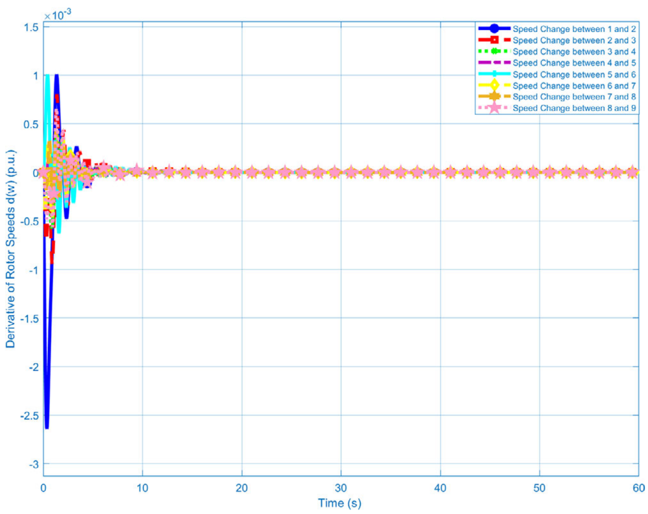

FIGURE 16 Derivative of rotor speeds using clustered coordination

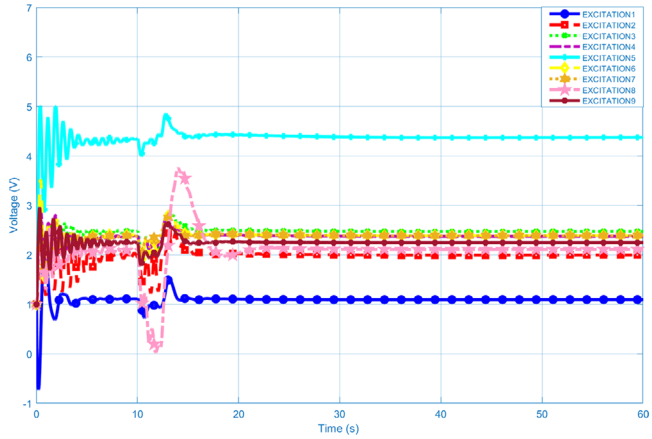

FIGURE 17 Field excitation using no coordination

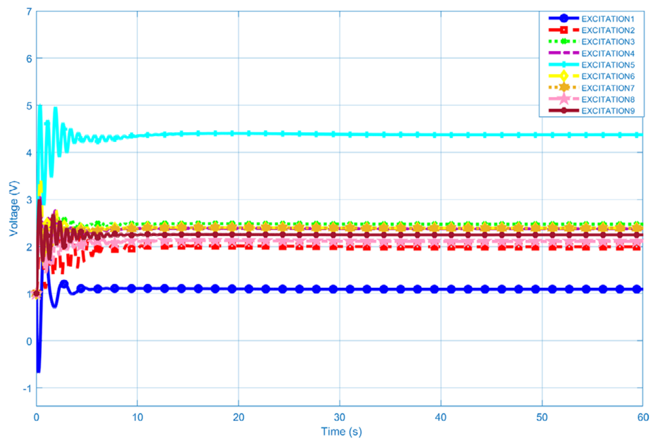

FIGURE 18 Field excitation using clustered coordination

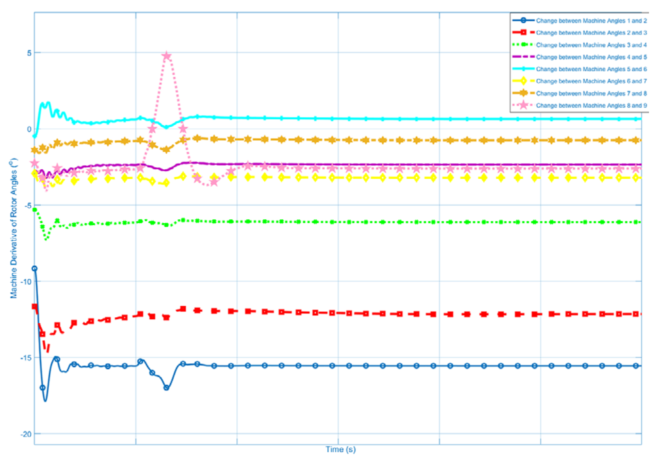

FIGURE 19 Machine angles using no coordination

0.42 s. This rise time is 0.238 s slower than the rise time of the MPC controller.

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

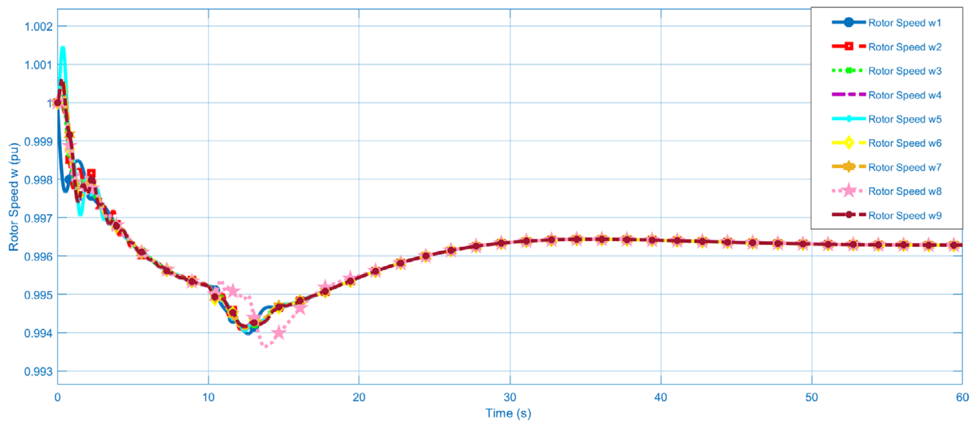

FIGURE 20 Rotor speeds using no coordination

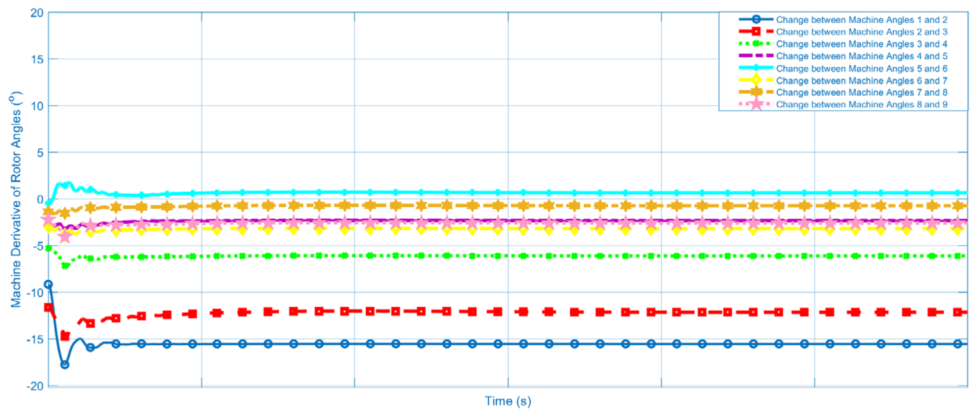

FIGURE 21 Machine angles using clustered coordination

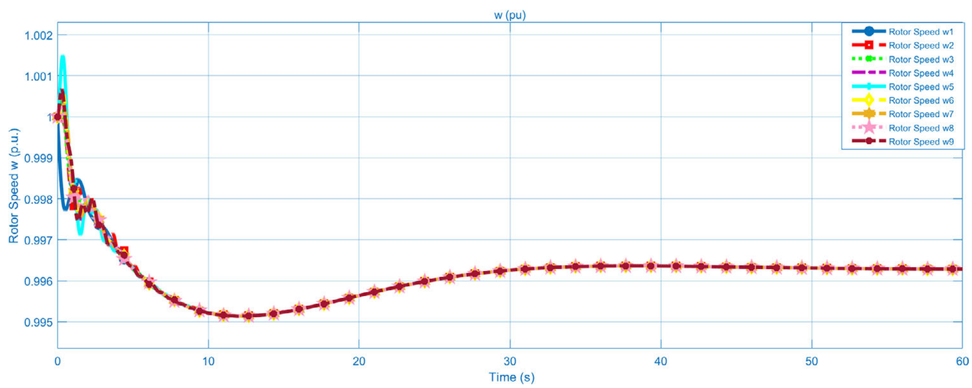

FIGURE 22 Rotor Speeds using clustered coordination

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

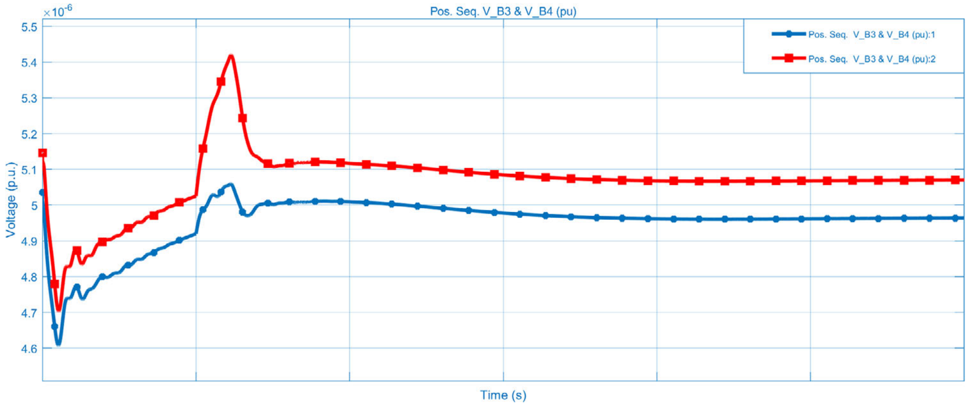

FIGURE 23 System voltages using no coordination

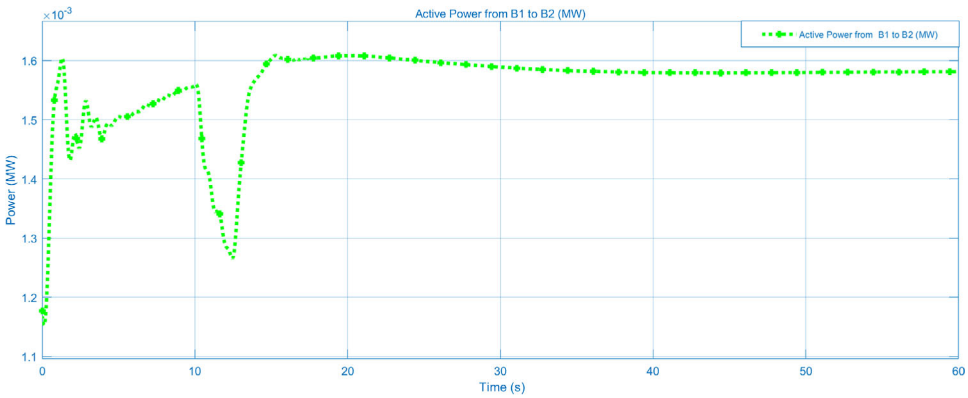

FIGURE 24 System real power using no coordination

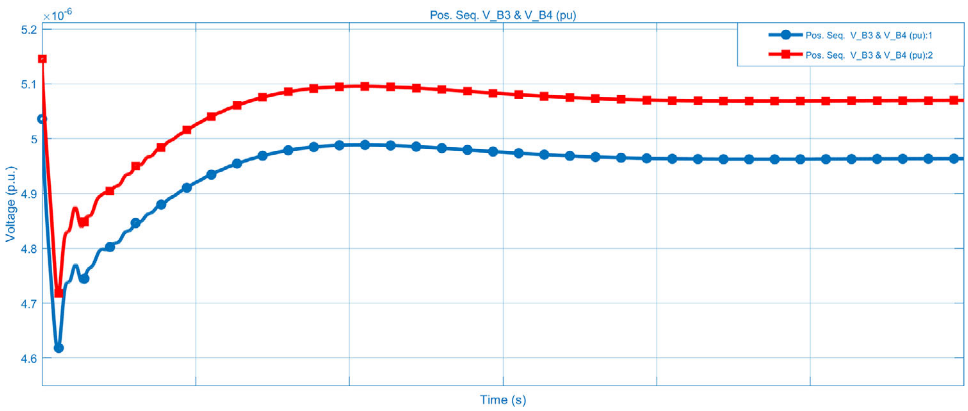

FIGURE 25 System voltages using clustered coordination

power grid system since it is a simplified model of the power grid in the New England area. 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

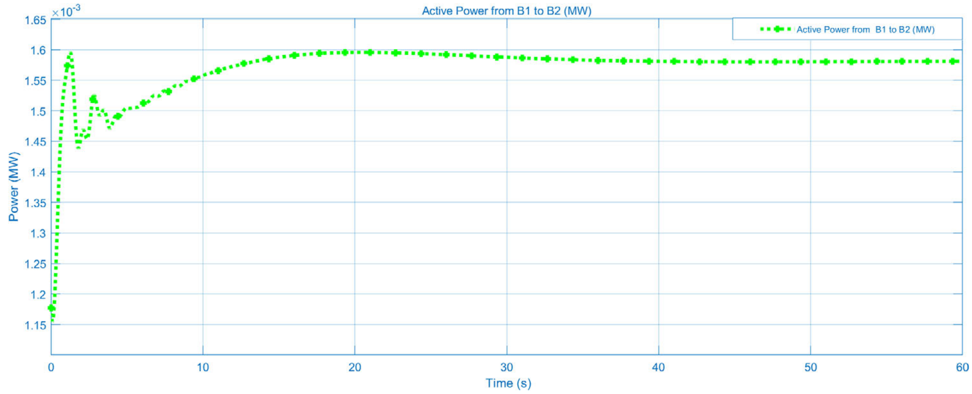

FIGURE 26 System real power using clustered coordination

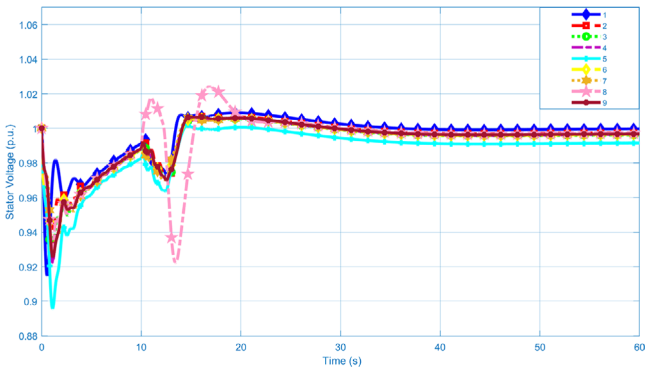

FIGURE 27 Stator voltages using no coordination

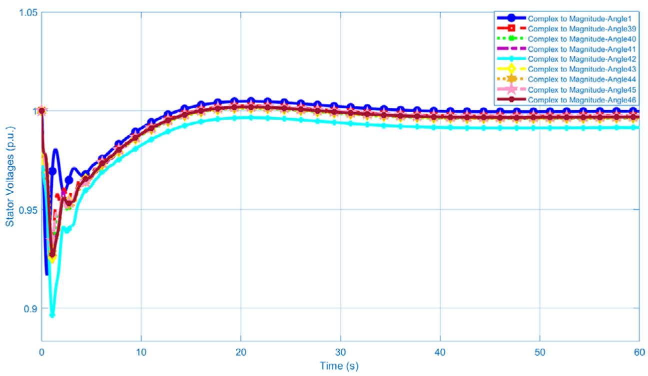

FIGURE 28 Stator voltages using clustered coordination

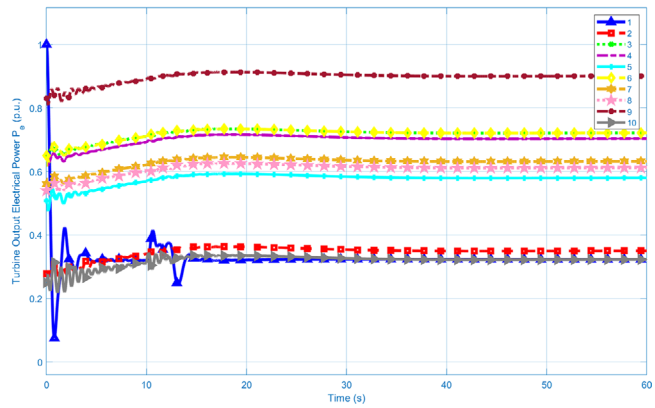

FIGURE 29 Turbine real power using no coordination

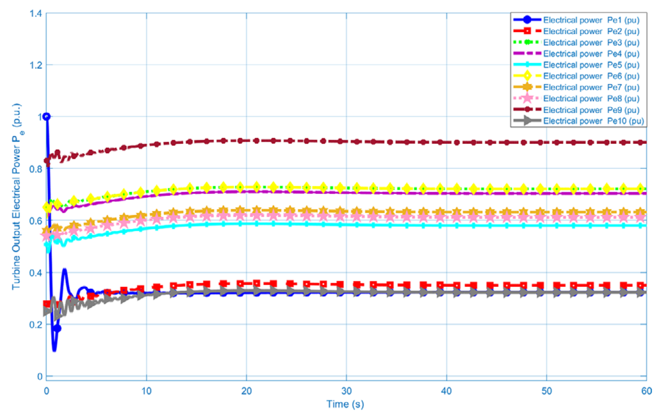

FIGURE 30 Turbine real power using clustered coordination

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 AVRs 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

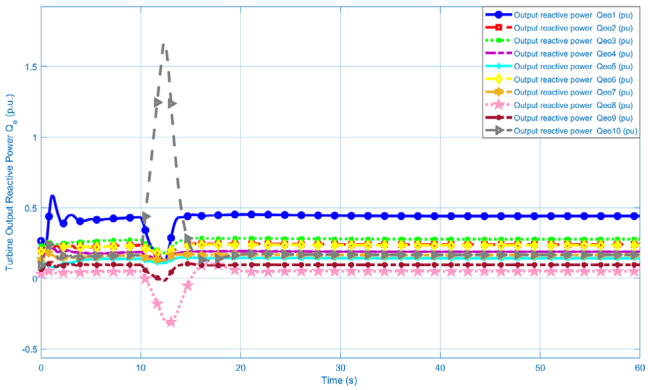

FIGURE 31 Turbine reactive power using no coordination

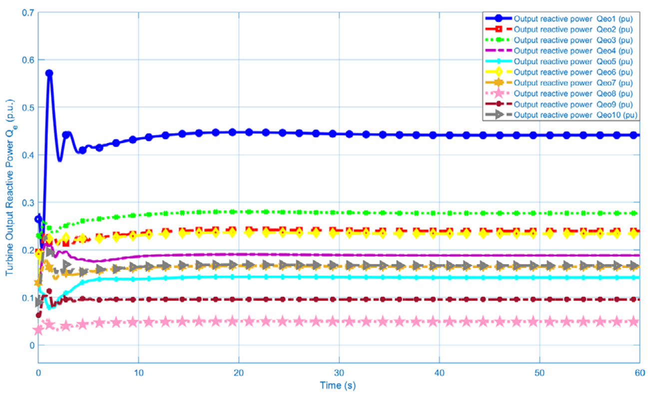

FIGURE 32 Turbine reactive power using clustered coordination

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_{PEAK}	Peak voltage
V_{REF}	Reference voltage
APSO	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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REFERENCES

1. Hasanien, H.M.: Design optimization of PID controller in automatic voltage regulator system using Taguchi Combined Genetic Algorithm method. IEEE Syst. J. 7(4), 825–831 (2013)
2. Selvabala, B., Devaraj, D.: Co-ordinated tuning of AVR-PSS using differential evolution algorithm. Paper presented at the 2010 Conference Proceedings IPEC, Singapore (2010)
3. Devaraj, D., Selvabala, B.: Real-coded genetic algorithm and fuzzy logic approach for real-time tuning of proportional–integral–derivative controller in automatic voltage regulator system. IET Gener. Transm. Distrib. 3(7), 641–649 (2009)
4. Kim, K., Rao, P., Burnworth, J.A.: Self-tuning of the PID controller for a digital excitation control system. IEEE Trans. Ind. Appl. 46(4), 1518–1524 (2010)
5. Rahimian, M.S., Raahemifar, K.: Optimal PID controller design for AVR system using particle swarm optimization algorithm. Paper presented at the 24th Canadian Conference on Electrical and Computer Engineering, Niagara Falls, ON (2011)
6. Nirmal, J.F., Auxillia, D.J.: Adaptive PSO based tuning of PID controller for an automatic voltage regulator system. Paper presented at the International Conference on Circuits, Power and Computing Technologies, Nagercoil, India (2013)
7. Bayram, M.B., Bülbül, H.İ., Can, C., Bayindir, R.: Matlab/GUI based basic design principles of PID controller in AVR. Paper presented at the 4th

International Conference on Power Engineering, Energy and Electrical Drives, Istanbul, Turkey (2013)
8. Li, Y., Wu, S.: Controlled islanding for a hybrid AC/DC grid with VSC-HVDC using semi-supervised spectral clustering. IEEE Access. 7, 10478–10490 (2019)
9. Yin, L., Luo, S., Wang, Y., Gao, F., Yu, J.: Coordinated complex-valued encoding dragonfly algorithm and artificial emotional reinforcement learning for coordinated secondary voltage control and automatic voltage regulation in multi-generator power systems. IEEE Access. 8, 180520–180533 (2020)
10. Zhang, M., Li, J., Li, Y., Xu, R.: Deep learning for short-term voltage stability assessment of power systems. IEEE Access. 9, 29711–29718 (2021)
11. Yin, L., Zhang, C., Wang, Y., Gao, F., Yu, J., Cheng, L.: Emotional deep learning programming controller for automatic voltage control of power systems. IEEE Access. 9, 31880-31891 (2021)
12. Kose, E.: Optimal control of AVR system with tree seed algorithm-based PID controller. IEEE Access. 8, 89457–89467 (2020)
13. Ou, T.-C., Tsao, T.-P., Hong, C.-M., Chen, C.-H.: Hybrid control system for automatic voltage regulator in smart grid. Paper presented at the International Conference on Machine Learning and Cybernetics, Tianjin, China (2013)
14. Gupta, T., Sambariya, D.K.: Optimal design of fuzzy logic controller for automatic voltage regulator. Paper presented at the International Conference on Information, Communication, Instrumentation and Control, Indore, India (2017)
15. Hekimoğlu, B., Ekinci, S.: Grasshopper optimization algorithm for automatic voltage regulator system. Paper presented at the 5th International Conference on Electrical and Electronic Engineering, Istanbul, Turkey (2018)
16. Madruga, E.P., Canha, L.N.: Allocation and integrated configuration of capacitor banks and voltage regulators considering multi-objective variables in smart grid distribution system. Paper presented at the IEEE/IAS International Conference on Industry Applications, Sao Paulo, Brazil (2010)
17. Pereira, P., Canha, L., Milbradt, R., Abaide, A., Schmaedecke, S., Arend, G., Madruga, E.: Optimization of voltage regulators settings and transformer tap zones in distribution systems with great load variation using distribution automation and the smart grids initiatives. Paper presented at the 8th International Conference on the European Energy Market, Zagreb, Croatia (2011)
18. Zhang, X., Hodge, J., Attavvay, M.: Intelligent voltage regulator in smart grid distribution system. Paper presented at the China International Conference on Electricity Distribution, Shenzhen, China (2014)
19. Yalla, M.: Design of a new operating mode for voltage regulator controls in a smart distribution system. Paper presented at the IEEE Rural Electric Power Conference, Columbus, OH (2017)
20. Lujano-Rojas, J., Dufo-López, R., Bernal-Agustín, J., Domínguez-Navarro, J., Osório, G., Catalão, J.: Determining the optimal setting of voltage regulators for day-ahead management of distribution smart systems. Paper presented at the IEEE Manchester PowerTech, Manchester, UK (2017)
21. Sulaiman, S.M., Jeyanthy, P.A., Devaraj, D.: Big data analytics of smart meter data using adaptive neuro fuzzy inference system. Paper presented at the International Conference on Emerging Technological Trends, Kollam, India (2016)
22. Canha, L.N., Pereira, P.R., Antunes, M.: Smart voltage regulator to active voltage level management of distribution networks. CIRED - Open Access Proc. J. 2017(1), 855–859 (2017)
23. Canha, L.N., Pereira, P.R., Milbradt, R., d R Abaide, A., Schmitt, K.E.K., Antunes, M.d.A.: Intelligent voltage regulator to distributed voltage control in smart grids. Paper presented at the 52nd International Universities Power Engineering Conference, Heraklion, Greece (2017)
24. Abegaz, B.W.: Dynamic switching control of buck converters using unsupervised machine learning methods. IET J. Eng. 2020(12), 1155–1164 (2020)
25. Abegaz, B., Kueber, J., Smart control of automatic voltage regulators using K-means clustering, 2019 14th Annual Conference System of Systems Engineering (SoSE), 2019, pp. 328–333, https://doi.org/10.1109/SYSOSE.2019.8753873
26. Abegaz, B.W.: Stability improvement of power networks using cluster based dynamic excitation of AVR, 2019 IEEE 10th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), 2019, pp. 0791–0795, https://doi.org/10.1109/UEMCON47517.2019.8992959

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