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Genetic Algorithm Based Data-Driven ILQR Control Scheme for Three-Phase Microgrid System

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Abstract : **This paper introduces an integrator augmented linear quadratic regulator (ILQR) control platform for improvedoperation of a three-phase microgrid (MG) system. The threephase MG system operated with LQR control scheme, often suffers from instability and poor performance during load shifting and the system transition period, while the proposed control scheme, ILQR, ensures stability and reduces the steadystate error of the system. The controller parameters have been tuned using a data-driven evolutionary optimization algorithm, genetic algorithm (GA). A comparison has been shown between the performance of GA optimized LQR and GA optimized ILQR control scheme. The proposed GA optimized ILQR scheme has shown significant improvement with 0% steady-state error while LQR has shown 3.15%. GA optimized ILQR has also ensured 3.1% overshoot, while LQR scheme made 10.4% overshoot. Matlab and Simulink platform have been used for simulations and optimization.**

Index Terms—Microgrid, linear quadratic regulator (LQR), stability, integrator, controller optimization, genetic algorithm (GA)

I. INTRODUCTION

In the days to come, meeting power demand due to the depletion of natural resources and reducing the massive emission of CO2 from the burning of fossil fuels will be a significant challenge. The concept of MG and its integration with distributed renewable resources may provide an appealing solution to these problems. MG promises a controllable, reliable, and sustainable power generation.

In the definition of MG, it can be stated that- MG is a low voltage electrical power network consisting of distributed generating units, storage devices, and local loads to facilitate a local area such as suburban area, or any commercial facility [1]. MG can be operated both off-grid, and on-grid mode. In on-grid mode, MG is connected to the main grid with a point of common coupling where the grid dominates the MG system voltage and frequency [2]. MG also has the ability to go off-grid when the main grid fails to meet power demand which is also known as islanded MG operation. An islanded MG has many issues regarding control, and it differs from the conventional grid due to the variable nature of renewable generations. Renewable generation variations may result from various environmental factors like solar irradiation, wind speed, weather condition, etc. [3]. These variations in MG may lead to oscillations and poor quality of power. Hence, proper control and power management is required.

MG control has attracted many researchers and engineers. Various control approaches have been proposed and implemented in this field of MG control. In [4] droop control approach has been proposed for the parallel inverter operation in MG. Addressing the load parameter variations hierarchical control approach has been proposed in [5]. In [6], a PID based control scheme has been presented with an extensive survey on smart grid power converter applications.

Apart from classical control, many researches have been proposed on optimal control for MG. In [7], an LQR based controller has been proposed to stabilize the MG system transition from on-grid to off-grid. In [8], an LQR based optimal solution to frequency regulation and active power-sharing has been presented. Both of these LQR implementations have limitations for certain model situations. Model variations or uncertainties are not addressed in these works.

Controller tuning with the proper parameters is another challenge to get the desired performance. Many intelligent controller optimization approaches may be found in the literature. In [9] PID controller has been optimized with PSO for steam generator predictive control. In another work of the wind turbine [10], the GA has been used to optimize the pitch angle controller. These works motivates the implementations of GA with LQR in this proposed controller.

Among many controllers, LQR promises to give optimal state-feedback solutions by minimizing certain quadratic objective functions. The integration of integrator control with LQR can contribute to enhancing system reference tracking as well as system steady-state error handling capability.

This paper represents a comparison between the conventional LQR control approach and ILQR approach optimized by genetic algorithm, an intelligent optimization method, for obtaining system stability and improved performance. It consists of five sections. With the introduction in the section I, section II describes the system model. Section III illustrates the controller design and optimization algorithms. Section IV evaluates the optimizer as well as the controller performance with the system. Finally, a conclusion has been made in section V.

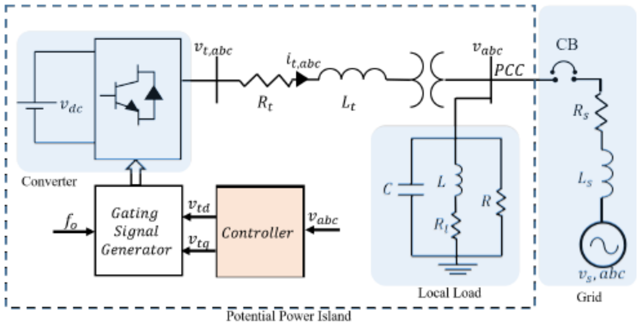


Fig. 1. Three-phase MG system model

II. System Description

A. System Model

A three-phase MG system as shown in Fig.1 has been considered in this paper for modeling, analysis, and performance evaluation. Different parameters of the system have been summarized in Table I.

Here a dc source with constant voltage has been used to represent the distributed resources. It has been connected to a voltage source inverter. The generated three-phase power has been passed into the transformer through an RL line filter and fed to a local load. A point of common coupling (PCC) has bridged the MG with the grid. In off-grid mode, the PCC acts as an isolator between MG and the main grid. Our proposedcontroller takes in the three-phase voltage and current and generates the required gate pulse.

Table I Parameters of the MG

Quantity	Value
R_t	$1.5m\Omega$
L_t	$300\mu\Omega$
$f_{pwmcarrier}$	$1980Hz$
VSC power rating	$2.5MW$
V_{load}	$600V$
R	76Ω
L	$111.9mH$
C	$62.85\mu F$
f_{res}	$60Hz$
R_s	1Ω
L_s	$10mH$
Grid SCR at PCC	19.
$f_{grid-nominal}$	$60Hz$
Transformer rating	$2.5MVA$
Voltage (DC source)	1500

$$
\begin{aligned}
v_{t,abc} &= L_t\frac{di_{t,abc}}{dt} + R_l i_{t,abc} + v_{abc}\\
i_{t,abc} &= C\frac{dv_{abc}}{dt} + i_{L,abc} + \frac{v_{abc}}{R}\\
v_{abc} &= L\frac{di_{L,abc}}{dt} + R_l i_{L,abc}
\end{aligned}
\tag{1}
$$

In 1 $v_{t,abc}, i_{t,abc}, v_{abc}$ represents the 3×1 vector components of each individual phase quanities and v_t and v denotes terminal voltage and the load voltage respectively of Fig. 1. After transforming abc to the stationary $\alpha\beta$ framework we get (2).

$$
\begin{aligned}
di_{t,\alpha\beta} &= -\frac{R_t}{L_t}i_{t,\alpha\beta} - \frac{v_{\alpha\beta}}{L_t} + \frac{v_{t,\alpha\beta}}{L_t}\\
\frac{dv_{\alpha\beta}}{dt} &= \frac{1}{C}i_{t,\alpha\beta} - \frac{1}{RC}v_{\alpha\beta} - \frac{i_{L,\alpha\beta}}{C}\\
\frac{di_{L,\alpha\beta}}{dt} &= \frac{v_{\alpha\beta}}{L} - \frac{R_l}{L}i_{L,\alpha\beta}
\end{aligned}
\tag{2}
$$

Performing a stationary $\alpha\beta$ to rotating dq reference based framework on (2) gives us (3).

$$
\begin{aligned}
\frac{di_{t,dq}}{dt} + j\omega i_{t,dq} &= -\frac{R_t}{L_t}i_{t,dq} - \frac{v_{dq}}{L_t} + \frac{v_{t,dq}}{L_t}\\
\frac{dv_{dq}}{dt} + j\omega v_{dq} &= \frac{1}{C}i_{t,dq} - \frac{1}{RC}v_{dq} - \frac{i_{L,dq}}{C}\\
di_{L,dq} + j\omega i_{L,dq} &= \frac{v_{dq}}{L} - \frac{R_l}{L}i_{L,dq}
\end{aligned}
\tag{3}
$$

Letting $v_q = 0$ makes $\dot{v_q} = 0$. Therefore (3) leads to the following deduction (4).

$$
\begin{aligned}
\frac{di_{td}}{dt} &= -\frac{-R_t}{L_t}i_{td} + \omega i_{tq} - \frac{v_d}{L_t} + \frac{v_t d}{L_t}\\
\frac{di_{td}}{dt} &= -\omega i_{td} - \frac{-R_t}{L_t}i_{tq} + \frac{v_{tq}}{L_t}\\
\frac{di_{Ld}}{dt} &= -\frac{-R_t}{L_t}i_{Ld} + \omega i_{Lq} + \frac{1}{L}v_d\\
\frac{di_{Lq}}{dt} &= -\omega i_{Ld} - \frac{R_l}{L}i_{Lq}\\
\frac{dv_d}{dt} &= \frac{1}{C}i_{td} - \frac{1}{C}i_{Ld} - \frac{1}{RC}v_d\\
\omega C v_d &= i_{tq} - i_{Lq}
\end{aligned}
\tag{4}
$$

State Space model, representing the system dynamics of the MG system, is given by (5).

$$
\begin{aligned}
\dot{X(t)} &= AX(t) + bu(t)\\
y(t) &= cX(t)\\
u(t) &= v_{td}
\end{aligned}
\tag{5}
$$

where,

$$A = \begin{bmatrix} -\frac{R_t}{L_t} & \omega_0 & 0 & -\frac{1}{L_t} \\ \omega_0 & -\frac{R_t}{L} & -2\omega_0 & \frac{R_l C\omega_0}{L} - \frac{\omega_0}{R} \\ 0 & \omega_0 & -\frac{R_t}{L} & \frac{1}{L} - \omega_0^2 C \\ \frac{1}{C} & 0 & -\frac{1}{C} & -\frac{1}{RC} \end{bmatrix}$$

$$B = [\tfrac{1}{L_t} \quad 0 \quad 0 \quad 0]$$

$$C = [0 \quad 0 \quad 0 \quad 1]$$

$$X^T = [i_{td} \quad t_{tq} \quad i_{Ld} \quad v_d]]$$

The nominal plant transfer function can be obtained after substituting the system parameter as Eq. (6).

$$g_n(s) = \frac{33150s^2 + 208300s + 4.71e9}{s^4 + 220.6s^3 + 177700s^2 + 3.09e7 + 4.86e9} \qquad (6)$$

III. Principle Of Control Algorithm

This section describes the concepts related to the design of the LQR and the ILQR controller and its optimization process with GA.

1) Linear Quadratic Regulator (LQR) Control: LQR is an optimal regulatory control. In this control design, a state feedback gain K is designed such that the cost function J gets minimized. Here, some compromises are made between the system stability performance and the controller effort. For a continuous-time linear system dynamics described as Eq. (7)

$$\dot{x} = Ax + Bu, y = Cx + Du \quad (7)$$

The cost function of the LQR is given by Eq. (8)

$$J = \int_0^{\infty} [x(t)^T Q x(t) + u(t)^T R u(t)] dt \qquad (8)$$

where the weight matrix Q is a positive definite or positive semi-definite symmetry matrix and R is a positive definite symmetry matrix. The feedback law is given by Eq.(9) that minimizes the cost function.

$$u = -kx \qquad (9)$$

where K is given by Eq. (10) and P is derived from the solution of the algebraic riccati equation Eq.(11).

$$K = R^{-1}B^{T}P \qquad (10)$$

$$A^{T}P + PA + Q - PBR^{-1}B^{T}P = 0 \qquad 11)$$

The LQR control approach with GA is illustrated in Fig.2.

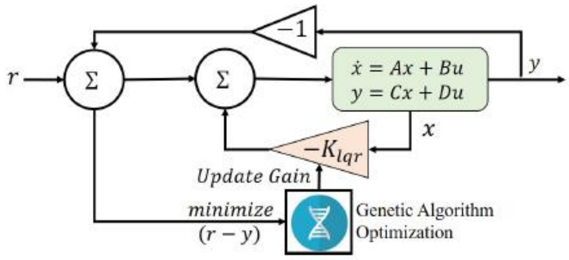


Fig. 2. LQR control architecture with GA

2) Integrator Augmented Linear Quadratic Regulator (ILQR) Control: Any system struggling from the steady-state error can be improved with the help of integral action. Augmenting an integral action with the system and implementing an LQR controller can provide more stability and robustness to a system. With the concept of integral augmentation, the controller proposed in this paper has been optimized with GA as illustrated in Fig. 3.

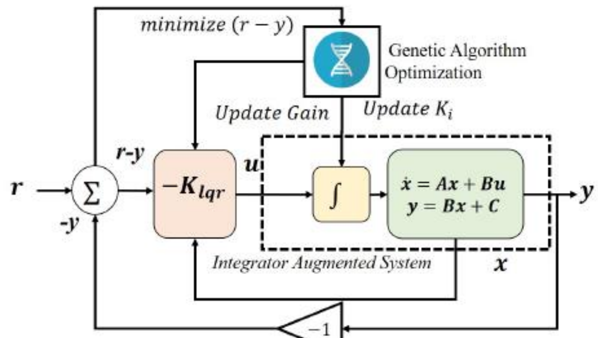


Fig. 3. Proposed ILQR control architecture with GA

A. Controller Optimization: Genetic Algorithm Performance of a controller depends greatly on proper tuning of controller parameters. Most of the time, trial and error method based tuning is employed for improving controller performance which is not always the optimal one. Different data-driven optimization methods e.g. GA can come into action to solve this problem. With proper objective function GA can introduce improvement in controller design.

Tuning a controller with Genetic Algorithm (GA) is an iterative process. GA, introduced by Holland (1975) [11], is a stochastic optimization method for solving problems based on natural selection and biological evolution. The main operations of GA are- selection, crossover, and mutation. Selection directs the search to the best individuals. Strings that has high fitness, get multiple copies, while fewer or no copies are derived from strings with less fitness in the next generation. Crossover provides a mechanism to produce desirable qualities using theproper exchange of chromosome properties in the mating pool. Mutation provides a random alteration of a bit in the string to keep diversity in the population. The process of GA is illustrated in Fig. 4.

The optimization parameters has been set as shown in Table.II

The GA optimization has been used in this paper to properly tune the controllers in order to minimize the steady-state error function. The objective function for GA is also based on integral time absolute error (ITAE) Eq. (12).

$$J_{min} = \int_0^{\infty} t|r(t) - y(t)|dt \tag{12}$$

IV. Performance Analysis

A. Optimization Results

With the focus on achieving minimum steady-state error and proper reference tracking, both LQR and ILQR controllers have been tuned with GA optimization separately. Their optimization fitness performance can be observed with LQR and ILQR controller, respectively, in Fig. 5(a) and 5(b).

The GA optimized ILQR has shown better improved performance than GA optimized LQR in regards to steady-state error correction, overshoot minimization with a minor trade off of setting time. The optimized parameters for the LQR and ILQR controller are shown Table III.

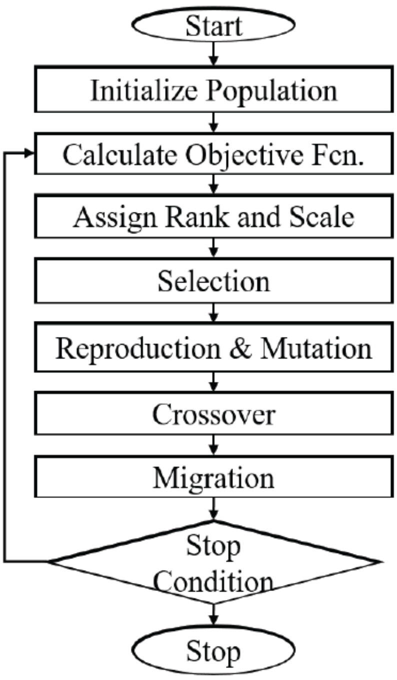


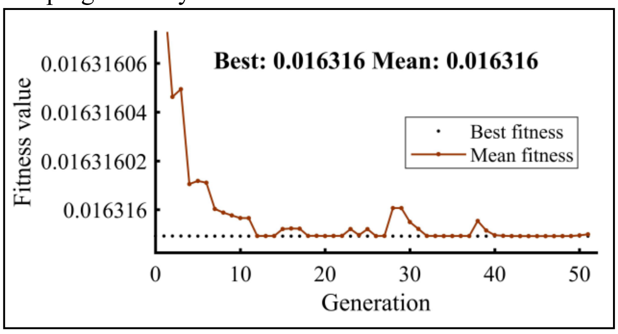
Fig. 4. Flow chart of genetic algorithm

Table II GA Optimization Parameters

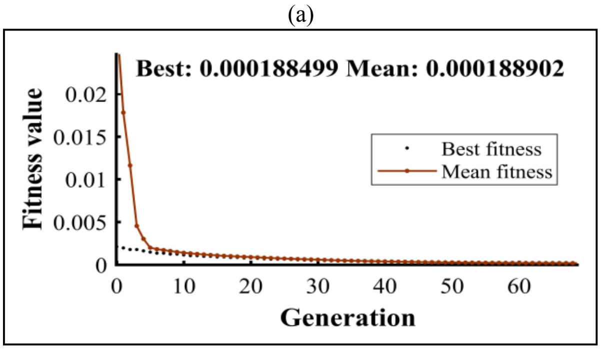
Parameters	Setup value
Types of Optimization	Single Objective Optimization (unconstrained minimization problem)
Population Size	50
No of variables	5 for LQR [Q11,Q22,Q33,Q44,R] 7 for ILQR [Q11,Q22,Q33,Q44,Q55,R,Ki]
Lower Bound of Variables	For LQR $[1, 1, 1, 1, 0.001]$
Upper Bound of Variables	For LQR $[\infty, \infty, \infty, \infty, 1]$
Lower Bound of Variables	For ILQR $[1, 1, 1, 1, 1, 0.001, 1]$
Upper Bound of Variables	For ILQR $[\infty, \infty, \infty, \infty, \infty, 1, \infty]$
Fitness Scaling Function	Rank Based
Selection Function	Stochastic Uniform
Reproduction	Elite count: 0.05x Pop. Size Crossover fraction: 0.8
Mutation function	Gaussian (as no constraints considered)
Crossover function	Scattered (as no linear constraints considered)
Migration	Direction: Forward Fraction: 0.2 Intervals: 20
Stopping Criteria	Generation: 100x no. of Var. Function Tolerance: 1e-6

B. Reference Tracking

The system has been tested with several types of test signals and reference signals. The impulse response of any system reveals the reaction of that system to any abrupt changes brought to its input. This also shows how fast a system recovers the system from any transients. Fig. 6 shows the impulse response of the both system with LQR and ILQR controller. It is evident from the response that ILQR has brought better stability with improved damping in the system.



(a)



(b)

Fig. 5. GA fitting curves for (a) LQR (b) ILQR

Table III Optimized Controller Parameter

LQR with GA						
Q11	Q22	Q33	Q44	R	-	-
17.483	33.257	18.734	8.007	0.947	-	-
Proposed ILQR with GA						
Q11	Q22	Q33	Q44	Q55	R	Ki
12.588	5.464	14.071	22.578	6.456	0.06258	62.931

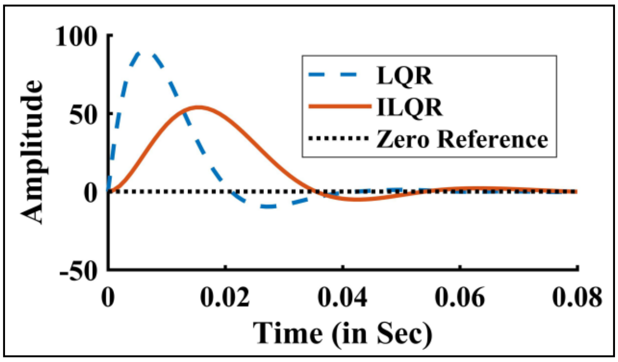
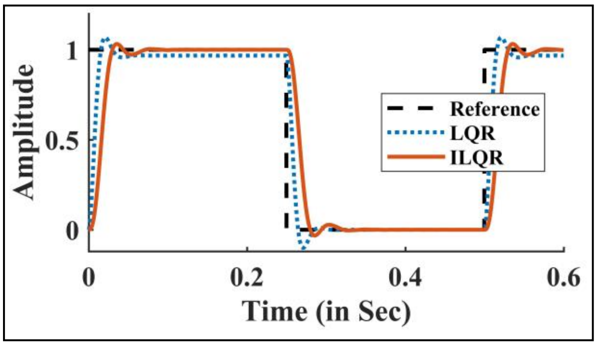
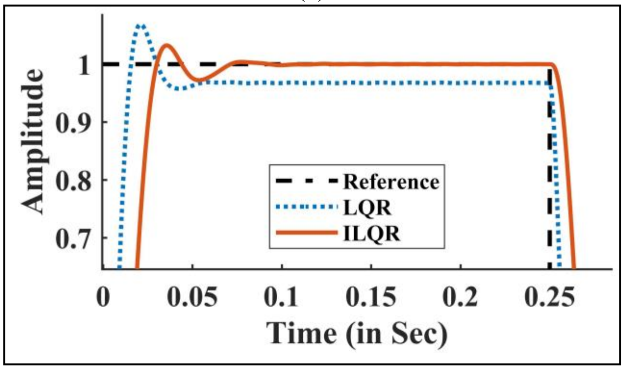


Fig. 6. Impulse response of LQR vs. ILQR

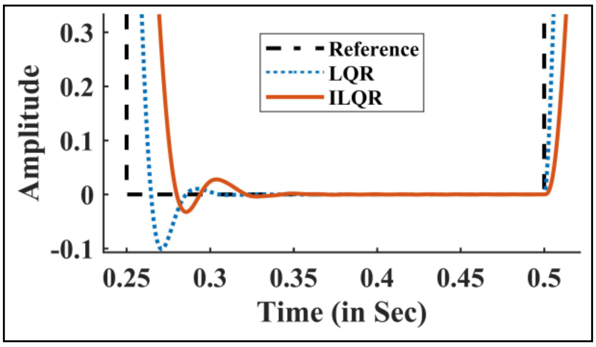
For reference tracking, here a square wave test signal has been applied. The simulated results are presented in Fig. 7. The obtained step performance is given in the Table IV.



(a)



(b)



(c)

Fig. 7. (a) Step response to square wave reference signal (b) top zoom View (c) bottom zoom view

Table IV System Step Response With Optimized Controller

Step Response	LQR Controller	Proposed ILQR Controller
Steady-state error	3.15%	0 %
Overshoot	10.4659%	3.1662 %
Rise time	0.01 s	0.01 s
Settling time	0.0319 s	0.0617 s

V. Conclusion

A dynamic model of a three-phase MG system with a GA optimized ILQR control approach has been presented in this paper. The proposed controller design approach has been tested for reference tracking with optimized parameters.With a comparison between a GA optimized LQR and GA optimized ILQR, it has been shown that an ILQR has better performance for reference tracking and handling overshoot. Integral control action has provided extra stability and error correction for the system.

This paper is limited to only GA optimization, which can be extended to other modern optimization methods e.g., ANN, PSO, ant colony optimization etc. Also, the controller has been designed using LQR, which can be further extended to other robust and adaptive controllers. LQR/ ILQR controller approach has one major limitation that it requires all states of the system to be measurable. With a well modeled system LQR/ ILQR can be one of the best candidate for controller design. For system with immeasurable states it is best to switch other controller with observer e.g., LQG.

References

[1] R. H. Lasseter, "Microgrids," in 2002 IEEE Power Engineering Society Winter Meeting. Conference Proceedings (Cat. No. 02CH37309), vol. 1. IEEE, 2002, pp. 305–308.

[2] D. E. Olivares, A. Mehrizi-Sani, A. H. Etemadi, C. A. Ca˜nizares, R. Iravani, M. Kazerani, A. H. Hajimiragha, O. Gomis-Bellmunt, M. Saeedifard, R. Palma-Behnke et al., "Trends in microgrid control," IEEE Transactions on smart grid, vol. 5, no. 4, pp. 1905–1919, 2014.

[3] M. Mazidi, A. Zakariazadeh, S. Jadid, and P. Siano, "Integrated scheduling of renewable generation and demand response programs in a microgrid," Energy Conversion and Management, vol. 86, pp. 1118– 1127, 2014.

[4] E. Planas, A. Gil-de Muro, J. Andreu, I. Kortabarria, and I. M. de Alegr´ıa, "General aspects, hierarchical controls and droop methods in microgrids: A review," Renewable and Sustainable Energy Reviews, vol. 17, pp. 147–159, 2013.

[5] X. Lu, J. M. Guerrero, K. Sun, J. C. Vasquez, R. Teodorescu, and L. Huang, "Hierarchical control of parallel ac-dc converter interfaces for hybrid microgrids," IEEE Transactions on Smart Grid, vol. 5, no. 2, pp. 683–692, 2013.

[6] I. Colak, E. Kabalci, G. Fulli, and S. Lazarou, "A survey on the contributions of power electronics to smart grid systems," Renewable and Sustainable Energy Reviews, vol. 47, pp. 562–579, 2015.

[7] D. Das, G. Gurrala, and U. J. Shenoy, "Linear quadratic regulator-based bumpless transfer in microgrids," IEEE Transactions on Smart Grid, vol. 9, no. 1, pp. 416–425, 2016.

[8] Y. Khayat, M. Naderi, Q. Shafiee, Y. Batmani, M. Fathi, J. M. Guerrero, and H. Bevrani, "Decentralized optimal frequency control in autonomous microgrids," IEEE Transactions on Power Systems, vol. 34, no. 3, pp. 2345–2353, 2018.

[9] S. Bassi, M. Mishra, and E. Omizegba, "Automatic tuning of proportional-integral-derivative (pid) controller using particle swarm optimization (pso) algorithm," International Journal of Artificial Intelligence & Applications, vol. 2, no. 4, p. 25, 2011.

[10] Z. Civelek, "Optimization of fuzzy logic (takagi-sugeno) blade pitch angle controller in wind turbines by genetic algorithm," Engineering Science and Technology, vol. 23, no. 1, pp. 1–9, 2020.

[11] M. Mitchell, "An introduction to genetic algorithms mit press," Cambridge, Massachusetts. London, England, 1996.