https://doi.org/10.31436/iiumej.v27i1.3944

Optimizing Energy Efficiency in Three-Phase Induction Motors via GWO-Tuned PID Control

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(Received: 13 September 2025; Accepted: 3 December 2025; Published online: 12 January 2026)

ABSTRACT: Induction motors consume a significant share of industrial electricity, making their efficiency a crucial aspect of sustainable energy management. Traditional Proportional–Integral–Derivative (PID) controllers are commonly used to regulate motor performance; however, their fixed parameters often fail to maintain optimal control under varying load conditions. Although optimization methods, such as Genetic Algorithms and Particle Swarm Optimization, have been introduced to enhance PID tuning, they often encounter challenges, including premature convergence and limited adaptability. This creates a clear need for an optimization strategy that is both robust and dynamically responsive to ensure energy-efficient motor operation. To address this gap, this study introduces a Grey Wolf Optimization (GWO)-based PID tuning strategy that distinguishes itself from existing methods by achieving a superior adaptive balance between exploration and exploitation. This characteristic enables the controller to maintain stable, responsive performance even under fluctuating load conditions. Experimental results confirm that the proposed GWO-PID controller successfully reduces motor current from 285.21 A to 164.2 A and lowers power consumption from 150 kW to 84.5 kW, achieving a 42.4% reduction in current and a 44.7% improvement in energy efficiency. Additionally, electricity costs decrease by 43.5%, demonstrating strong economic potential. The novelty of this research lies in integrating GWO's adaptive intelligence with PID control, yielding a more effective, reliable, and energy-efficient solution than existing optimization-based controllers for industrial induction motor systems.

ABSTRAK: Motor aruhan menggunakan sebahagian besar tenaga elektrik industri, menjadikan kecekapan operasi satu aspek penting dalam pengurusan tenaga mampan. Pengawal konvensional Kadar-Integral-Pembezaan (PID) lazim digunakan bagi mengawal prestasi motor; namun, parameter tetapnya sering gagal mengekalkan kawalan optimum di bawah keadaan beban berubah. Walaupun kaedah pengoptimuman seperti Algoritma Genetik dan Pengoptimuman Kawanan Partikel telah diperkenalkan bagi menambah baik talaan PID, pendekatan ini sering menghadapi masalah penumpuan awal dan keupayaan adaptasi yang terhad. Hal ini memerlukan satu strategi pengoptimuman yang lebih mantap dan responsif secara dinamik bagi memastikan operasi motor cekap tenaga. Bagi menangani masalah ini, kajian ini memperkenalkan satu strategi talaan PID berasaskan Pengoptimuman Serigala Kelabu (Grey Wolf Optimization, GWO) yang menonjol dari kaedah sedia ada melalui keseimbangan adaptifnya yang unggul pada penerokaan dan pengeksploitasian. Ciri ini membolehkan pengawal mengekalkan prestasi stabil dan responsif walaupun berkeadaan beban yang berubah. Dapatan kajian melalui eksperimen menunjukkan bahawa pengawal GWO–PID yang dicadangkan ini berjaya mengurangkan arus motor daripada 285.21 A kepada 164.2 A dan menurunkan penggunaan kuasa daripada 150 kW kepada 84.5 kW—

https://doi.org/10.31436/iiumej.v27i1.3944

mencapai pengurangan arus sebanyak 42.4% dan peningkatan kecekapan tenaga sebanyak 44.7%. Selain itu, kos elektrik turut menurun sebanyak 43.5%, sekaligus membuktikan potensi ekonomi yang kukuh. Keunikan kajian ini terletak pada integrasi kecerdasan adaptif GWO dengan kawalan PID, menawarkan penyelesaian lebih berkesan, boleh dipercayai, dan cekap tenaga berbanding pengawal berasas pengoptimuman lain bagi sistem motor aruhan industri.

KEY WORDS: *Induction motor, Proportional–Integral–Derivative (PID) control, Grey Wolf Optimization (GWO), Energy Efficiency, Power Reduction*

1. INTRODUCTION

Three-phase induction motors (IMs) are the most widely deployed electromechanical energy-conversion devices in industrial practice, driving pumps, compressors, conveyors, and numerous manufacturing systems. Their simplicity, robustness, low cost, and ease of maintenance make them the preferred choice over synchronous or DC machines in a wide range of applications. However, this ubiquity comes with significant energy implications: IMs are estimated to account for nearly 70% of industrial electrical demand and approximately 40% of total global electricity consumption, positioning them at the core of both industrial productivity and sustainability challenges [1][2]. Given the urgent global transition toward low-carbon technologies, improving the efficiency of IM operations has become an essential focus for reducing greenhouse gas emissions, lowering operational costs, and meeting energy conservation targets.

Despite their prevalence, induction motors rarely operate under-rated; instead, they often experience variable loads and fluctuating supply conditions that degrade performance and reduce efficiency. Energy losses, originating from stator and rotor copper losses, core losses, stray load losses, and frictional effects, are further exacerbated by conventional control strategies. Traditional methods, such as constant-voltage–constant-frequency operation or manually tuned Proportional–Integral–Derivative (PID) controllers, cannot maintain optimal efficiency across diverse load profiles. Even modest efficiency improvements, if realized at scale, could yield substantial reductions in industrial energy consumption and costs [3][4]. This highlights the need for adaptive control strategies that can maintain efficiency in real-world operating conditions.

Recent research has explored several efficiency-oriented control approaches for IMs. Scalar/vector methods, such as loss-model control or flux optimization within field-oriented control (FOC) and direct torque control (DTC), adjust flux and voltage to minimize losses; however, they are sensitive to parameter variations and may sacrifice dynamic response for efficiency [5][6]. Predictive control strategies integrate efficiency terms directly into cost functions, achieving rapid transients and measurable input power reductions, but at the expense of computational complexity and sensitivity to modeling errors [7][8]. More recently, metaheuristic-assisted tuning of PID controllers, using algorithms such as Genetic Algorithm (GA) [9][10], Particle Swarm Optimization (PSO) [11][12], Differential Evolution (DE) [13][14], Whale Optimization Algorithm (WOA) [15][16], Artificial Bee Colony (ABC) [17], and Grey Wolf Optimization (GWO), has emerged as an attractive alternative [18]-[20]. These methods are gradient-free, robust to multimodal objectives, and compatible with legacy PID-based drives, thereby enabling efficiency improvements without overhauling the control architecture.

Within this family, GWO has gained attention due to its balance between exploration and exploitation, minimal parameter requirements, and adaptability to both online and offline optimization. Studies have demonstrated GWO's effectiveness in improving dynamic performance metrics, such as overshoot, settling time, torque ripple, and Total Harmonic Distortion (THD), across power systems and electrical machines, including induction motors and induction generators [6][11]. However, most of these studies prioritize dynamic response over explicit energy-efficiency metrics, such as reducing input power, copper and iron losses, or improving efficiency under partial-load conditions. Additionally, PID optimization methods with GWO for induction motor energy efficiency are rarely evaluated in real-time experimental setups. Conversely, methods explicitly designed for efficiency (e.g., loss-model or predictive controllers) have shown promising energy savings but rarely leverage the flexibility of metaheuristic PID tuning under real industrial load variations [5][6].

Motivated by these limitations, this study investigates the integration of PID control with GWO to optimize energy efficiency in a practical industrial setting. The research focuses on a 150 kW three-phase induction motor used in water distribution at PT Tirta Asasta Depok, Indonesia, a representative case of large-scale industrial energy use. Unlike previous works, the proposed approach formulates a multi-objective optimization function that directly incorporates efficiency and loss minimization alongside conventional stability and tracking criteria. The contribution of this work lies in bridging the gap between theory and practice, demonstrating, through both MATLAB simulations and real-world industrial implementations, that GWO-tuned PID controllers can significantly improve energy metrics, including power factor, reactive power, current draw, and active power consumption. Beyond technical performance, the results reveal substantial reductions in operational costs, highlighting the practical feasibility of metaheuristic-based efficiency optimization in industrial motor systems.

The remainder of this paper is organized as follows: Section 2 presents the theoretical background and methodology, including the PID controller structure and the design of the GWO algorithm. Section 3 describes the simulation and experimental setup. Section 4 discusses the results and performance comparisons. Section 5 concludes with key findings and recommendations for future work.

2. MATERIAL AND METHOD

2.1. Materials

The primary equipment used in this study consisted of a Variable-Speed Drive (VSD) and a three-phase induction motor. The motor employed was a TECO-brand end-suction (centrifugal) unit with a rated power of 150 kW, a rated current of 285 A, and a nominal speed of 1500 rpm. To regulate its operation, a 220 kW VSD was utilized, providing precise control over motor performance. For measurement, a digital ammeter was used to record the current in real time. At the same time, a Schneider Human-Machine Interface (HMI) served as the monitoring platform for displaying motor parameters and validating measurements against both manual calculations and digital ammeter readings.

2.2. Methods

The proposed system integrates a Supervisory Control and Data Acquisition (SCADA) platform with the Variable Speed Drive (VSD) to control the three-phase motor. The optimization process is carried out by tuning the Proportional-Integral-Derivative (PID) controller parameters using the Grey Wolf Optimization (GWO) algorithm. The experimental procedure is summarized in the research methodology diagram presented in Figure 1.

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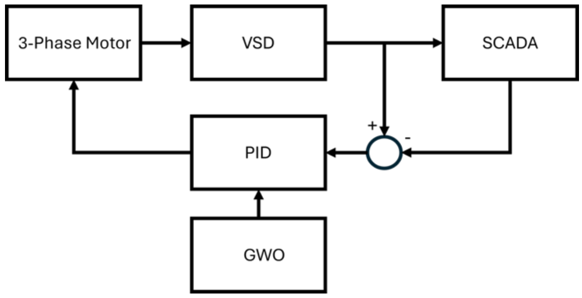

Figure 1. Proposed Research Methodology.

The methodology can be described in the following steps:

1. The system operates using a single three-phase induction motor connected to a Variable Speed Drive (VSD).
2. Each critical parameter, voltage, current, power factor (*cos φ*), and frequency, is measured using corresponding sensors integrated into the VSD. These sensors generate real-time signals, which are transmitted to the SCADA system via a data acquisition (DAQ) module and the Modbus TCP/IP protocol.
3. The SCADA system records and monitors these parameters continuously. The collected data are used for two primary purposes: (a) PID parameter tuning and (b) optimization of those PID parameters using the Grey Wolf Optimizer (GWO) algorithm.
4. During the optimization process, the SCADA system provides closed-loop feedback by sending the real-time measurements to the controller, which updates the control signals to the VSD. The feedback loops ensure that the PID and GWO algorithms receive accurate, instantaneous data for decision-making and adjustment.
5. The SCADA interface displays all measured and control parameters, including current, voltage, frequency, power factor, and motor switching status, enabling real-time supervision and performance analysis.
6. Finally, system performance is evaluated by comparing the motor's operational characteristics before and after applying the GWO-optimized PID control. The comparison is based on metrics such as steady-state error, rise time, and energy efficiency.

This experimental setup enables the systematic monitoring, control, and optimization of motor energy efficiency, ensuring that results are both accurate and practically applicable.

2.2.1. Working System

The working principle of this research is illustrated through the control block diagram presented in Figure 2. The diagram depicts a closed-loop control system employing a Proportional-Integral-Derivative (PID) controller optimized using the Grey Wolf Optimizer (GWO) algorithm. The objective of this system is to ensure that the output closely follows the desired reference signal with high accuracy and stability.

At the core of the system, the reference input $R(s)$ in the Laplace domain specifies the target system response. This signal is continuously compared with the actual output $C(s)$ at the summing junction, producing an error signal $e(s)$. The error, defined as the difference between the reference and the actual output, is processed by the PID controller to generate a corrective control signal.

The PID controller regulates the system behavior using three parameters: proportional gain Kp, integral gain Ki, and derivative gain Kd. The proportional term responds to the present

https://doi.org/10.31436/iiumej.v27i1.3944

error, the integral term eliminates steady-state errors by accounting for past deviations, and the derivative term anticipates future errors to improve stability. Instead of conventional manual tuning, this study employs the GWO algorithm to optimize these parameters automatically.

The Grey Wolf Optimizer (GWO) is a metaheuristic algorithm inspired by the hunting strategy and leadership hierarchy of grey wolves. In this research, GWO is applied to search for the optimal PID parameter set by minimizing performance indices, including Integral Square Error (ISE), Integral of Time-weighted Absolute Error (ITAE), settling time, and overshoot. This optimization ensures efficient tuning and improves system performance without relying on heuristic or trial-and-error methods.

The optimized control signal is then applied to the plant $P(s)$, which represents the physical system being controlled, in this case, a three-phase induction motor. The plant is modeled mathematically using its transfer function in the Laplace domain. The resulting system output $C(s)$ is fed back into the summing junction, thereby completing the closed-loop configuration.

The mathematical relations used in this study are expressed as follows:

Synchronous speed:

$$ns = \frac{(120\times f)}{p} \tag{1}$$

where f is the frequency and p is the number of poles.

Power in terms of torque and speed:

$$P = \frac{(T\ x\ ns)}{5252} \tag{2}$$

Electrical power relation:

$$P = V\ x\ I\ x\cos\varphi \tag{3}$$

where P is the active power, V is the RMS voltage, I is the RMS current, and $cos\ \varphi$ is the Power factor, which is the ratio of active power to apparent power. φ is the phase angle between current and voltage. The primary optimization target is the power factor $cos\ \varphi$. For a three-phase induction motor, the default power factor is typically around 0.8. By optimizing the PID controller parameters using GWO, the power factor is improved, thereby enhancing overall energy efficiency.

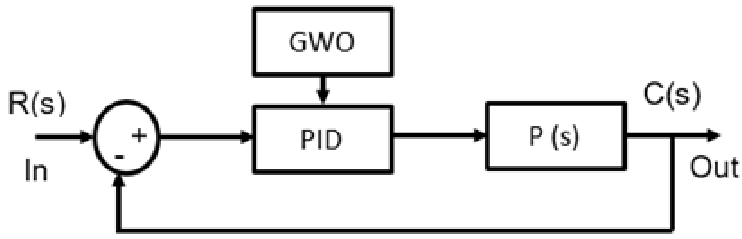

Figure 2. Control System Block Diagram.

In summary, the proposed system integrates classical control theory with modern optimization techniques to deliver a robust and efficient closed-loop controller. This integration is particularly advantageous for engineering applications that require high precision, rapid response, and system stability, such as electric motor drives, robotics, and industrial automation.

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2.2.2. Grey Wolf Optimizer (GWO)

The Grey Wolf Optimizer (GWO) was first introduced in [18] as a novel swarm intelligence (SI) algorithm. It has demonstrated competitive performance compared to other metaheuristic algorithms such as the Gravitational Search Algorithm (GSA) and Differential Evolution (DE). The GWO is inspired by the natural leadership hierarchy and cooperative hunting strategy of grey wolves (Canis lupus), apex predators in the animal kingdom. In the wild, wolves typically live in packs consisting of 5-12 individuals, maintaining a strict social hierarchy that governs their collective behavior.

The hierarchy consists of four levels. The alpha (α) wolves lead the pack and represent the best solution in the optimization process. The beta (β) wolves act as subordinate leaders, assisting the alpha in decision-making and strengthening the directives, while also offering alternative solutions. The delta (δ) wolves serve as scouts, sentinels, and hunters, supporting the alpha and beta wolves. Finally, the omega (ω) wolves occupy the lowest rank, representing the weakest solutions but playing a crucial role in maintaining diversity within the population.

The hierarchical structure of the grey wolf pack is illustrated in Figure 3. As shown, the alpha (α) wolf occupies the highest rank, symbolizing the best solution at a given iteration. The beta (β) wolves represent the second-best solutions, assisting the alpha in guiding the pack. The delta (δ) wolves, positioned below the beta, act as scouts, hunters, and protectors, contributing additional search diversity.

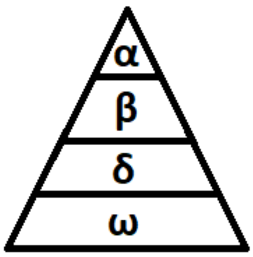

Figure 3. The hierarchical structure of GWO.

Finally, the omega (ω) wolves are located at the bottom of the hierarchy, corresponding to the weakest solutions. Despite their low ranking, omegas play a critical role in maintaining population balance and preventing premature convergence. This hierarchical model underpins the Grey Wolf Optimizer (GWO), in which leadership roles correspond directly to solution quality in the optimization process. During the optimization process, the hierarchy is mapped into the search mechanism as follows: the alpha (best), beta (second-best), and delta (third-best) wolves guide the population, whereas the omega wolves update their positions according to these leaders. This structure effectively balances exploration (global search) and exploitation (local refinement), mimicking the natural foraging behavior of wolves.

Mathematically, the encircling behavior is modeled as:

$$\vec{D} = \left|\vec{C} \,.\, \overrightarrow{Xp}(t) - \vec{X}(t)\right| \tag{4}$$

$$\vec{X}(t+1) = \vec{X}p(t) - \overrightarrow{A.D} \tag{5}$$

where t is the current iteration, X is the position vector of a grey wolf, and Xp denotes the prey position. The coefficient vectors A and C are calculated as:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{6}$$

https://doi.org/10.31436/iiumej.v27i1.3944

$$\vec{C} = 2.\vec{r}_2 \tag{7}$$

Here, r_1 and r_2 are random vectors in the range [0,1], while a decreases linearly from 2 to 0 over the course of iterations, thereby controlling the balance between exploration and exploitation. The three best solutions (α, β, δ) are retained at each iteration, and the positions of the remaining wolves (ω) are updated according to their influence:

$$\begin{aligned} \vec{D}\alpha &= \left|\vec{C}1 - \vec{X}\alpha - \vec{X}\right| \\ \vec{D}\beta &= \left|\vec{C}2 - \vec{X}\beta - \vec{X}\right| \\ \vec{D}\delta &= \left|\vec{C}3 - \vec{X}\delta - \vec{X}\right| \end{aligned} \tag{8}$$

$$\begin{aligned} \vec{X}1 &= \vec{X}\alpha - \vec{A}1.\vec{X}\alpha \\ \vec{X}2 &= \vec{X}\beta - \vec{A}2.\vec{X}\beta \\ \vec{X}3 &= \vec{X}\delta - \vec{A}3.\vec{X}\delta \end{aligned} \tag{9}$$

$$X(t+1) = \frac{X1+X2+X3}{3} \tag{10}$$

This formulation enables GWO to simulate the collaborative hunting strategy of grey wolves, ensuring that the population converges toward optimal or near-optimal solutions while efficiently exploring the search space.

2.2.3. PID with Grey Wolf Optimization (GWO)

The Grey Wolf Optimization (GWO) algorithm is applied to fine-tune the PID controller parameters, thereby optimizing the power factor (*cos φ*) of a three-phase induction motor, thereby reducing unnecessary power consumption and improving overall energy efficiency. The optimization process is illustrated in Figure 4.

As shown in Figure 4, the proposed methodology follows a closed-loop optimization process that integrates the GWO algorithm with the PID controller through continuous feedback. The process begins with initializing the three-phase motor and assigning initial Proportional, Integral, and Derivative (PID) parameters. The GWO algorithm is then executed to estimate an optimal parameter set through its leadership hierarchy, where X_α (Alpha wolf) represents the best candidate solution, X_β (Beta wolf) the second-best, and X_δ (Delta wolf) the third-best, while the remaining wolves (X_ω) explore the search space to maintain population diversity.

Each candidate PID parameter set is applied to the control loop, and the resulting system performance, such as error magnitude, power factor (*cos φ*), and voltage stability, is measured in real time via the SCADA system. This feedback is returned to the GWO algorithm to evaluate the fitness of each candidate solution. Based on this feedback, GWO iteratively updates its search direction and parameter estimates over multiple iterations (up to 100 cycles) until the convergence criterion is met. Once the optimal PID gains are achieved, the motor operates under the optimized configuration. During operation, the SCADA interface continuously monitors and displays real-time voltage, current, frequency, and power factor (*cos φ*). When the system stabilizes, a higher cos φ value (e.g., 0.92) indicates improved power quality and enhanced energy utilization.

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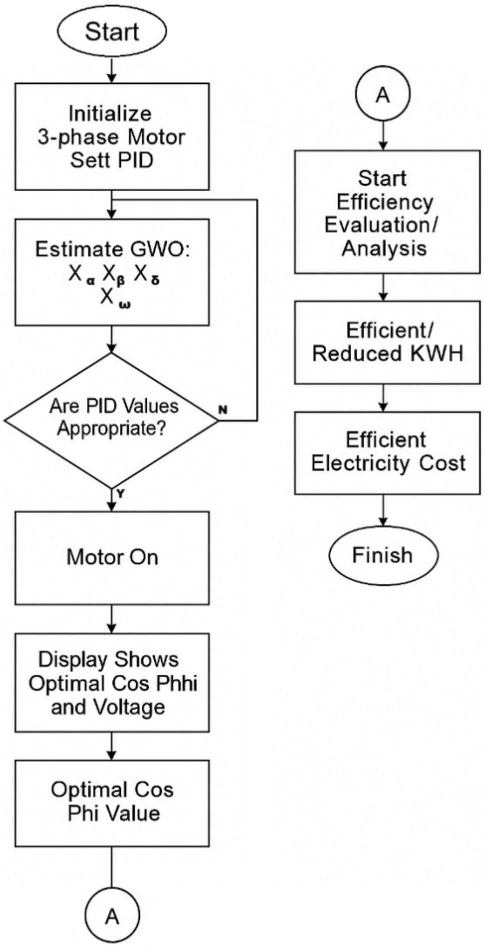

Figure 4. Optimization Flowchart Using Grey Wolf Optimization (GWO).

In the final stage, the system evaluates energy efficiency by comparing total power consumption (in kWh) before and after optimization, thereby quantifying the reduction achieved and the corresponding cost savings. This closed-loop GWO–PID integration confirms the feasibility of real-time adaptive tuning and demonstrates the potential scalability of this approach for multi-motor industrial systems.

2.2.4. Data Analysis Method

A quantitative analysis approach was employed to assess both the accuracy and performance of the proposed model. The evaluation process was carried out in two primary stages. First, model accuracy was verified by comparing the current measurements obtained from the digital ammeter (ampere clamp) with the values displayed on the Human-Machine Interface (HMI). This step ensured consistency between the measurement instruments and the system's monitoring display. From the theoretical perspective, the motor current can be calculated using the following equation:

$$I = \frac{P}{(V\ x \cos\varphi \times 1.73)} \tag{11}$$

Second, a power-loss analysis was conducted to quantify the energy-efficiency improvements. Manual calculations based on the power triangle formula were performed and compared with readings obtained directly from the ammeter clamp. Through this comparative assessment, the reliability of the proposed optimization method in reducing power loss and improving system efficiency was validated.

2.2.5. Energy and Cost Computation

To evaluate the practical benefit of the proposed optimization, monthly energy consumption and corresponding costs were computed using the average motor power consumption. The monthly energy consumption E was calculated using Eq. (12).

$$E = P \times t \times d \tag{12}$$

where P is the average motor power consumption (kW), t represents the operating hours per day, and d denotes the number of operating days per month. The associated monthly electricity cost C was then estimated as:

$$C = E \times R \tag{13}$$

where R is the electricity rate (USD/kWh). The computation provides a consistent framework to quantify the energy efficiency and cost savings achieved by the proposed PID–GWO control strategy.

3. RESULTS AND DISCUSSION

This section presents the experimental results and the subsequent discussion. The analysis compares the initial power factor (cos φ) with the improved values obtained by integrating Proportional–Integral–Derivative (PID) control with Grey Wolf Optimization (GWO). The outcomes are illustrated both graphically and in tabular form to ensure clarity and reproducibility. All results were derived from field measurements using standardized instruments, theoretical calculations, and Human–Machine Interface (HMI) monitoring. Each experiment comprised 100 GWO iterations to determine the optimal PID parameter set.

The subsequent subsections provide a detailed comparison between baseline and optimized performance, followed by an analysis of the impact of GWO-based tuning on motor efficiency.

3.1. Power Factor (*cos φ*) Optimization

The initial power factor of the three-phase induction motor fluctuated between 0.80 and 0.87, indicating suboptimal operating conditions and a higher reactive power demand. After applying the PID controller tuned using Grey Wolf Optimization (GWO), the power factor improved substantially, stabilizing near the target value of 0.92. This improvement corresponds to a relative enhancement of approximately 6-12% compared to the baseline condition.

Figure 5 depicts the simulation of GWO convergence over 100 iterations. The optimized PID parameters enabled the power factor to consistently approach the target value of 0.92. In contrast, the non-optimized case (without PID tuning) remained fixed at 0.80, highlighting the limited capability to self-correct under standard operating conditions.

The results demonstrate that integrating GWO into PID tuning provides a robust mechanism for compensating reactive power and improving overall motor efficiency. The algorithm's ability to dynamically adjust the PID gains contributes to its rapid convergence toward the reference value. This enhancement reflects a more efficient utilization of electrical power, as the optimized controller reduces the grid's reactive power demand. The Grey Wolf Optimization algorithm successfully converged to an optimal set of PID parameters after 100 iterations, yielding Kp = 11.2, Ki = 11.0, and Kd = 3.5. The convergence behavior of these parameters is illustrated in Figure 6.

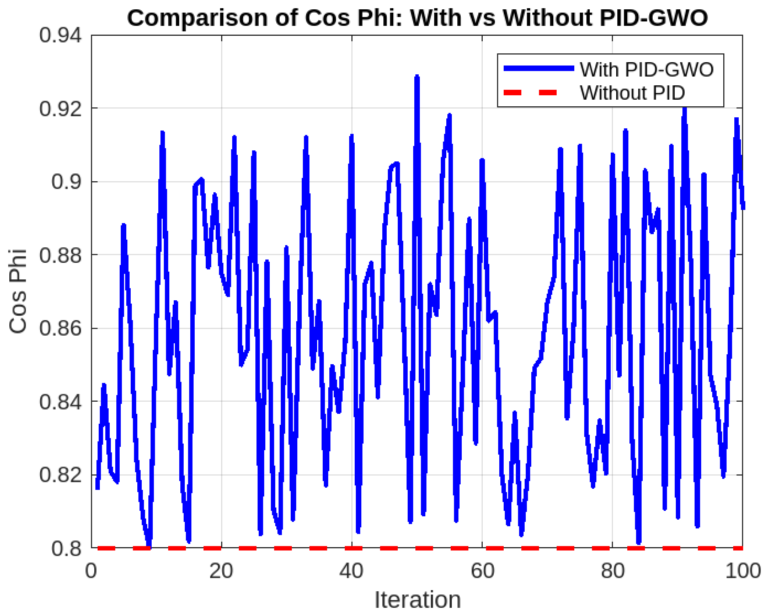

Figure 5. Cos phi with vs without PID GWO

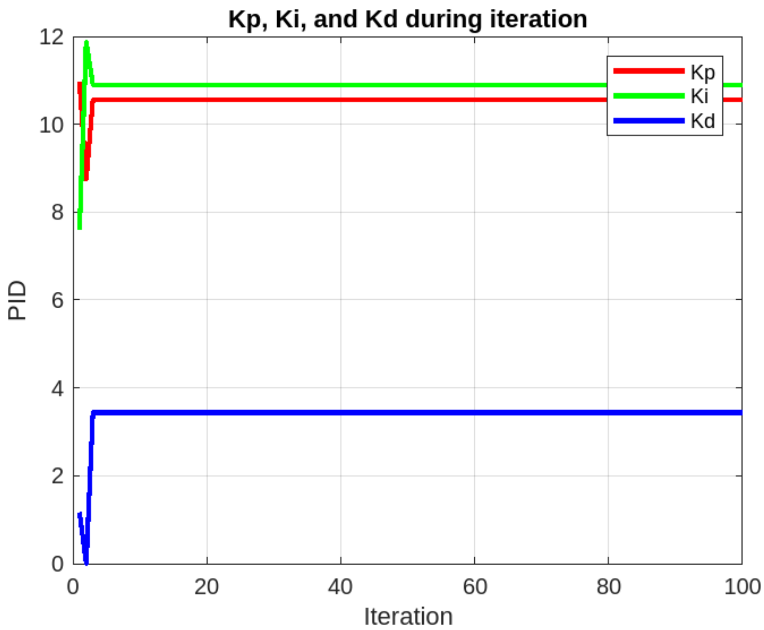

Figure 6. KP, KI, KD during iteration.

As shown in Figure 6, the three control gains experienced relatively large fluctuations during the early iterations, reflecting the exploration phase of GWO as it searches for the global optimum. After approximately 15 iterations, the parameters gradually stabilized, indicating a transition from exploration to exploitation. This steady convergence highlights GWO's ability to avoid local optima and ensure consistent tuning outcomes.

The PID-GWO configuration enabled the motor to maintain an average power factor close to the target value of 0.92. However, instantaneous values fluctuated between 0.80 and 0.93 during optimization, as illustrated in Figure 5. These fluctuations primarily reflect transient dynamics and the adaptive nature of the GWO-based tuning during load and iteration variations. Nevertheless, the optimized controller consistently improved the overall operating range of the power factor relative to the baseline (without PID), which remained nearly constant at approximately 0.80. From a practical standpoint, this demonstrates that the proposed PID-GWO control effectively minimizes reactive power demand and enhances system efficiency under dynamic operating conditions.

Following the determination of the optimal PID parameters, the next step was to implement them in practice on the Variable Speed Drive (VSD) via its Human–Machine Interface (HMI). The identified parameter values (Kp, Ki, and Kd) were manually entered into the HMI interface, as shown in Figure 7. This interface provides a direct means of adjusting the control gains that regulate key operational variables, including motor speed, pressure, and system stability. After parameter entry, measurements were conducted using standard instruments and theoretical validation. This step was crucial for verifying the accuracy of the optimized PID configuration obtained from the GWO algorithm.

Figure 7. PID Control parameters

Figure 8. A Real-time Cos phi Measurement after optimization

The results of the field implementation are presented in Figure 8. The optimized controller increased the power factor from approximately 0.82 to a stable 0.92, closely matching the target set during the optimization phase. This outcome not only validates the simulation results but also confirms the capability of the proposed PID–GWO approach to deliver consistent performance under real operating conditions.

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From an industrial standpoint, achieving a power factor of 0.92 represents a substantial improvement in energy efficiency, as it reduces reactive power demand and lowers operational costs. These findings highlight the practical feasibility of integrating metaheuristic optimization into existing control infrastructures, thereby bridging the gap between theoretical research and applied engineering practice.

3.2. Current Reduction

The implementation of the optimized PID controller resulted in a significant reduction in motor current. Initially, the pump motor was operating at 285.21 A as depicted in Figure 9. The figure presents the real-time simulation display using the available Human-Machine Interface (HMI). The interface inherently includes control panels and monitoring tabs that visualize both the control process and the current waveform simultaneously. This integrated view is intentionally maintained to reflect the actual implementation of the proposed PID-GWO method in the experimental environment. The current waveform indicates improved system response and stability following optimization. After optimization, the motor current was reduced to approximately 164.2 A (Figure 10-12).

This reduction directly decreases the I^2R copper losses, thereby improving overall thermal efficiency, reducing heat stress on the windings, and extending the equipment's operational lifespan.

Figure 9. Current without PID GWO

Figure 10. Current with PID GWO

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Figure 11. Current with PID GWO (clamp ammeter)

Figure 12. Current with PID GWO (HMI)

The verification of the motor current was performed using four independent measurement approaches: Human Machine Interface (HMI), Supervisory Control and Data Acquisition (SCADA) system, clamp meter readings, and the theoretical reference obtained from (11). All four approaches consistently indicated a motor current of approximately 164.1 A, confirming the accuracy and synchronization of both the monitoring and control systems. The agreement among these methods validates the reliability of the data acquisition infrastructure and demonstrates the effectiveness of the PID-GWO optimization in maintaining current stability under varying load conditions.

In addition to validating the current reduction, the HMI and SCADA interfaces provide real-time data regarding motor speed, frequency, and power, while the clamp meter measurement offers manual confirmation. The strong correlation between all four methods ensures the reliability of the monitoring infrastructure and validates the effectiveness of the PID optimization.

3.3. Active Power Reduction

The motor's active power consumption experienced a significant reduction, decreasing from 150 kW to 84.5 kW, as summarized in Table 1. This improvement was achieved by lowering the operating frequency from 50 Hz to 43.5 Hz, thereby aligning the pump operation with the actual load demand rather than maintaining the nominal rated condition.

This theoretical result shows an excellent agreement with the Modbus TCP/IP-recorded value of 84.3 kW, confirming the validity of both the measurement and the monitoring system. The consistency between the analytical estimation and SCADA observation demonstrates the reliability of the instrumentation in capturing real-time pump operating conditions.

The reduction in active power underscores the direct impact of optimized PID-based control, which not only lowers electrical demand but also improves energy efficiency and reduces operational costs. Such optimization strategies are particularly relevant for water treatment and distribution systems, where pumps typically account for the majority of total energy consumption.

Table 1. Power comparison with and without PID GWO

Frequency (Hz)	Power without PID-GWO (kW)	Power with PID-GWO (kW)
45.4	150	91.03
44.9	150	88.30
43.5	150	84.54
43.0	150	81.29
42.0	150	77.72
41.4	150	75.49
40.0	150	70.53
39.0	150	67.05

3.4. Energy Efficiency Analysis

Energy efficiency was evaluated as the ratio between the motor's output power and the corresponding input power. Following the optimization process, the efficiency improved substantially, reaching 44.77%.

Table 2 provides a detailed comparison of the motor current under three configurations: (i) without control, (ii) with conventional PID, and (iii) with PID tuned using the GWO algorithm. An additional column presents the Theoretical Current (A), calculated from the electromagnetic torque-supply voltage relationship described in (11). The results indicate that the measured current values obtained using the proposed PID–GWO controller closely follow the theoretical predictions across all frequency ranges, with only minor deviations (<0.2%) attributed to measurement noise and inverter nonlinearities. In contrast, the system without control consistently draws higher current, confirming that the PID–GWO approach effectively minimizes motor current and enhances overall system efficiency. This consistency between the experimental and theoretical results further validates the robustness and accuracy of the proposed control method.

https://doi.org/10.31436/iiumej.v27i1.3944

Table 2. Current comparisons with vs without PID GWO

Frequency (Hz)	Current without PID GWO (A)	Current with PID GWO (A)	Current with PID GWO (Amperemeter) (A)	Theoretical Current (A)
45.40	285.21	169.40	169.40	169.28
44.90	285.21	166.15	166.15	166.15
43.50	285.21	164.20	164.20	161.54
43.00	285.21	160.70	160.40	160.33
42.00	285.21	157.12	157.00	157.12
41.40	285.21	154.88	154.70	154.37
40.00	285.21	149.64	149.60	149.15
39.00	285.21	145.90	145.90	145.42

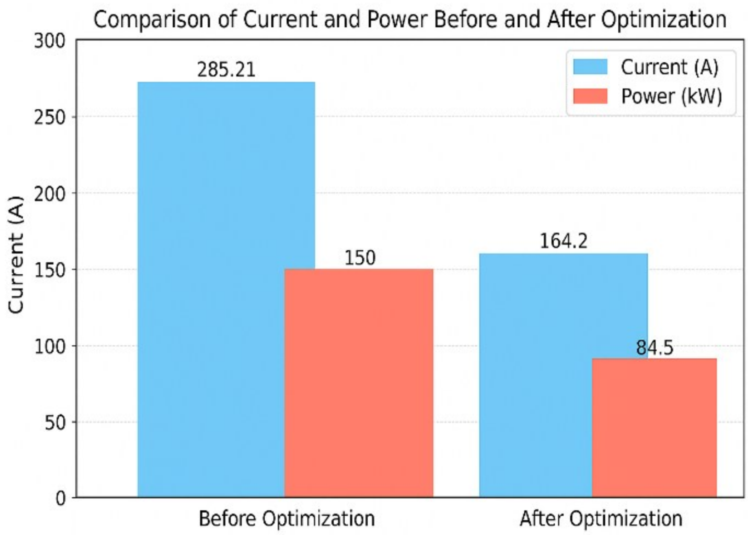

Figure 13. Comparison of current and power before and after Optimization

Figure 13 further illustrates the contrast in electrical performance before and after optimization. Before optimization, the motor consumed 285.21 A and delivered 150 kW, indicating excessive energy consumption under unoptimized conditions. After optimization, the current dropped significantly to 164.2 A and the active power to 84.5 kW, corresponding to reductions of approximately 42.4% in current and 44.7% in active power.

This marked reduction demonstrates that the PID-GWO optimization strategy not only enhances energy efficiency but also improves system reliability by reducing thermal stress on motor windings and lowering reactive power demand. Moreover, the resulting energy savings translate into reduced operational costs and a smaller environmental footprint, both of which are critical considerations in sustainable industrial practices.

3.5. Cost Analysis

In addition to the technical performance improvements, the energy efficiency and cost benefits of the proposed PID–GWO optimization strategy were evaluated under identical operating conditions. The computation results summarized in Table 3 show that the optimization significantly reduced the average power consumption from 150 kW to 84.5 kW.

This reduction corresponds to a monthly energy savings of 47,016 kWh, representing an approximately 43.5% improvement in energy efficiency. Assuming an average industrial electricity rate of USD 0.10 per kWh, the monthly operating cost decreased from USD 10,800 to USD 6,098, resulting in an estimated monthly cost savings of USD 4,702.

Table 3. Monthly Energy Consumption and Cost Analysis

Condition	Average Power (kW)	Monthly Energy (kWh)	Cost (USD 0.10/kWh)	Savings (%)
Before Optimization	150	108,000	10,800	-
Afer Optimization	84.5	60,984	6,098	43.5
Improvement	-	47,016	4,702	43.5

These findings confirm that the proposed control method not only enhances power quality and system stability but also yields substantial operational savings, resulting in a rapid return on investment (ROI). Moreover, the observed energy reduction contributes directly to sustainability goals by lowering overall energy demand and environmental impact.

3.6. Discussion

The experimental results presented in this study provide comprehensive evidence of the novel contribution and effectiveness of the proposed PID–GWO optimization approach in enhancing motor performance, improving energy efficiency, and reducing operational costs.

Unlike conventional PID controllers that rely on manual or heuristic tuning, the proposed method employs the Grey Wolf Optimizer (GWO) to automatically identify optimal proportional, integral, and derivative gains. This adaptive optimization process enables the controller to balance system stability and energy efficiency simultaneously, representing a significant improvement over traditional tuning methods.

As summarized in Table 2, the motor current decreased substantially after optimization. Without control, the system consumed approximately 285.21 A, whereas with the PID–GWO optimization, the current dropped to around 164.2 A, corresponding to a 42.4% reduction. This reduction directly correlates with improved power utilization and reduced electrical stress on motor components. Theoretical calculations align closely with the experimental data, confirming the accuracy and reliability of the optimized control design.

Energy efficiency, defined as the ratio of output to input power, also improved significantly. Before optimization, the motor operated at approximately 150 kW; after applying the PID–GWO controller, power consumption decreased to 84.5 kW, representing an energy-efficiency improvement of 44.77%. This improvement demonstrates that the optimized PID gains not only minimize transient deviations but also reduce continuous power losses, thereby stabilizing system performance under various load conditions.

The cost analysis further reinforces the practical relevance of the proposed optimization method. As presented in Table 5, the monthly electricity cost decreased from USD 10,800 to USD 6,098, yielding a monthly saving of USD 4,702, or approximately 43.5% reduction. This significant decrease in operational expenditure illustrates the dual benefit of the proposed PID–GWO scheme, delivering both technical and economic advantages suitable for real-world industrial environments.

These findings confirm that integrating GWO into PID control constitutes a novel hybrid optimization strategy capable of addressing multiple industrial challenges concurrently: reducing energy consumption, minimizing operational costs, and improving overall system stability. The demonstrated improvements are consistent with global sustainability objectives and energy efficiency directives, underscoring the method's potential for large-scale industrial adoption. Although the proposed approach yields substantial benefits, some limitations remain. This study primarily focused on steady-state operation. Future research should investigate dynamic load variations, fault tolerance, and scalability to different motor types and power ratings. Moreover, extending the optimization framework through hybridization with adaptive or learning-based algorithms could further enhance robustness and adaptability under fluctuating operating conditions.

In summary, the combined technical and economic evaluations clearly establish that the PID–GWO optimization introduces a novel, efficient, and practical solution for industrial motor energy management, bridging the gap between classical PID control and modern intelligent optimization techniques.

4. CONCLUSION

This study demonstrated the effectiveness of integrating PID control with Grey Wolf Optimization (PID-GWO) to enhance the performance and energy efficiency of a three-phase induction motor. The proposed method significantly reduced motor current by approximately 42.4% and improved energy efficiency by 44.77%. Additionally, the optimization yielded substantial financial benefits, reducing monthly electricity costs by nearly 43.5%. These results confirm that the PID-GWO approach is not only technically robust but also economically viable for industrial applications. Beyond cost and energy savings, the findings suggest broader implications for sustainable industrial operations, including reduced environmental impact through optimized energy consumption. Future research should focus on extending this approach to dynamic operating conditions, fault-tolerant systems, and hybrid optimization methods to further improve adaptability and scalability.

ACKNOWLEDGEMENT

This research was funded by the *Master Thesis Research Grant Scheme (Hibah Skema Penelitian Tesis Magister)* from the Ministry of Education, Higher Education, Science, and Technology of the Republic of Indonesia, under the fiscal year 2025. The authors would like to express their sincere gratitude for this financial support, which made the completion of this study possible.

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