Novel Adaptive Control Method for BLCD Drive of Electric Bike for Vietnam Environment

Chuong Nguyen Khanh¹, Sachintha Balasooriya¹, I Kavalchuk¹, A Kolbasov², K Karpukhin² and A Terenchenko²

¹ School of Science and Technology, RMIT University Vietnam, 702 Nguyen Van Linh, District 7, Tân Phong, Ho Chi Minh City, Hồ Chí Minh, Vietnam
² FSUE "NAMI", 2, Avtomotornaya Str., Moscow 125438, Russian Federation

Email: aleksey.kolbasov@nami.ru, ilya.kavalchuk@rmit.edu.vn

Abstract. Electric bikes are a rising mode of transportation in developing countries as their use reduce the use of hydrocarbon-based energy sources as well as increases convenience for the commuters within the city by reducing traffic. Furthermore, the electric bikes have low noise emission and no exhaust gases produced, which improves the environmental footprint. Due to the Vietnam regulations, most electric bikes use brushless wheel-hub motors as the main drivetrain solution paired with various types of batteries. The key challenges in the design of the drivetrains are related to the efficiency and controllability areas, so the response of the drivetrain can be improved. The key area of improvement lies in the control system design to optimize the performance and energy consumption. This paper presents the research done on developing of optimization PID control algorithms by using GA (Generic Algorithm) and PSO (Particle Swarm Optimization) for driving a synchronized brushless DC motor for the electric bikes.

1. Introduction

The use of electric vehicles has rapidly increased with the further development of cheap and reliable battery technologies for the needs of the transportation industry. Personal transportation has transitioned from the fossil-fuel driven solutions to fully or partially electric-powered vehicles for their lesser carbon footprint with the steady raise of the fuel prices [1]. Electric vehicles (EVs) also come with low maintenance costs since the transmission system is simpler than internal combustion engines [2]. These benefits have given rise to a demand for electric bikes which also has the added benefit of reducing traffic on the roads specially in highly populated areas as shown in [3], a study done on use of electric bikes in China over the last decade.

Due to the low power output and low driving range on a charge, electrification was raising in the applications of the motorbikes and scooters in the developing countries. The key technical benefit is the 95-98% efficiency of the wheel-hub electric drivetrain, in comparison with 25-30% efficiency of the small ICE in the scooters [4, 5]. As the higher efficiency is followed by reduction of the emissions, the government in China and Vietnam have been in favour of supporting electrification of the transport.
There are two common types of the electric motors used in EVs: synchronous AC motors and asynchronous AC motors, also known as inductive motors [6]. Brushed DC motors are not typically considered for this use case due to the sparking issues and lower efficiency. The synchronous brushless motors have either induced or pre-existing magnetic fields in the form of permanent magnets, especially for the low power applications. This requires the motor’s stator to provide the magnetic field that drives the motor in an ordered frequency/sequence, so the rotor can pick up the pace intended by the inverter, operated through the controller [7]. This requires the motor controller to have information on the speed of the rotor’s magnetic field, for the proper conditioning. Therefore, large scale synchronous AC motors have embedded hall sensors to track the magnetic field of the rotor [7]. Small brushless motors don’t require additional sensors, as their operation is based on the prediction of the rotor’s position by tracking it from the starting time by microcontroller, as shown in [8].

Brushless Direct Current Motors (BLDC) have several advantages in comparison with AC Induction motors for low-power electric bikes applications. Firstly, for a same power output, BLDC motor is 40-50% smaller in dimensions. For the two-wheeler application the drivetrain dimensions are the important consideration, especially for the wheel-hub motors, since it might springless masses reduction. Secondly, BLDC motor provides higher torque at low to middle speed range (0 – 2500 rpm) while AC Induction motor has larger torque at higher speed range (2500 – 3600 rpm). Considering city-based usage and that most residential areas in Ho Chi Minh city have the speed limit at 50 km/h, BLDC has low number of the drawbacks for the conditions. In addition, BLDC has 1-3% higher efficiency than AC Induction motor since its rotor is constructed with permanent magnets, and therefore, it possesses no copper losses ($I^2 R$) in the rotor [9, 10].

This paper analyses the performance requirement of a typical BLDC motor for electric bike application and presents an innovative control system design. Section two describes the system requirements and its mathematical model. Section three presents the developed control algorithm. Section four introduces methodology for optimization of the control algorithm for the city use of the vehicle. Section five gives the results of the developed system. Finally, the conclusion about the new system is given in section six.

2. System Definition and Modelling

Figure 1 shows the reference image of the proposed drivetrain architecture for the electric bike.

![Figure 1. Developed Architecture of the Electric Bike.](image)

The BLDC motor is installed at the rear wheel of the bike in order to improve the springless masses and the durability of the solution in the wet conditions, in comparison with the in-wheels architecture.

In order to develop adaptive control system, the mathematical model of the motor was derived in form of a block diagram. Figure 2 shows the mathematical model of the BLDC in form of a block diagram.
Based on Figure 2, the transfer function was obtained for the speed control versus supplied voltage:

\[
\frac{\omega(s)}{V_a(s)} = \frac{K_t}{L_a J_m s^2 + (L_a B_a + R_a J_m) s + R_a B_a + K_t K_b}
\]  

(1)

Table 1 shows the parameters for the transfer function from equation (1). Their values are deduced based on the choice of using Nc5000w BLDC motor and the weight of our bike of 100 kg, including batteries.

| Nomenclature | Parameter              | Value          |
|--------------|------------------------|----------------|
| \(K_t\)      | Torque constant        | 1.75 Nm/A      |
| \(K_b\)      | Back EMF constant      | 1.75 V/rad s^{-1} |
| \(R_a\)      | Electric resistance    | 1.38 Ω         |
| \(L_a\)      | Electric inductance    | 0.19 H         |
| \(B_m\)      | Friction coefficient   | 0.7 N.m        |
| \(J_m\)      | Moment of inertia      | 0.17 kg.m^2    |
| \(\omega\)   | Output angle           | N/A            |
| \(v_a\)      | Input voltage          | N/A            |

For the final mode, the values were substituted to the equation, so the final s-domain function was derived, as presented on (2):

\[
\frac{\omega(s)}{V_a(s) } = \frac{54.18}{(s^2+11.38s+124.72)}
\]  

(2)

The key requirements belong to the transient performance, as the specifications to react on the changing environment and input signals and keep the bike in the challenging traffic of the Ho Chi Minh city. Three identified parameters were chosen as overshoot (OS), raise time (Tr) and settling time (Ts) of 2% to ensure high accuracy to be achieved by the controller. The summary of the requirements for the BLDC motor used in the proposed motorbike is presented in Table 2. These parameters will be used to evaluate performance of the developed control system.
Table 2. - Transient Requirements of the system.

| Parameter | %OS | $T_r$ (s) | $2\%T_s$ (s) |
|-----------|-----|-----------|-------------|
| Values    | $\leq 2.5$ | $\leq 0.005$ | $\leq 0.01$ |

3. Development of Adaptive PID Controller for BLDC Motor

Fig. 3 shows the block diagram of the developed controller design. Here, the aim was to optimize the traditional PID controller by using adaptive control algorithms – either GA or PSO, as the optimizing algorithms with the low computational cost and its tunability. The output error is passed to the optimizer and computed in the cost function. The PID gains- $K_p$, $K_i$, $K_D$- that result in the least cost are substituted constantly to the real PID controller so that the system is accustomed to external disturbances.

This allows you to achieve the change in the performance of the drivetrain, based on the request from the accelerator and provide energy consumption optimization at the same time. Furthermore, the dynamics of the low-power solution allows it to stay in the traffic flow with the vehicles with higher power.

![Block Diagram of the Developed Adaptive PID Controller for BLDC Motor.](image)

A performance index or fitness function is an indication to performance of a system. In the context of GA and PSO optimizer, cost functions are usually used as performance indices. As mentioned previously, the error from motor’s output is accumulated in the cost function to be fed to the optimization block. Therefore, the smallest accumulated error – fitness value is equivalent to the best values of PID parameters which are used.

There are four commonly used performance indices for PSO and GA: Integral Square Error (ISE), Integral Absolute Error (IAE) and Integral Time Absolute Error (ITAE), Mean Squared Error (MSE), which can be calculated using equations (3)-(6) [11]:

\[
ISE = \int_0^T e(t)^2 \, dt \tag{3}
\]

\[
IAE = \int_0^T |e(t)| \, dt \tag{4}
\]

\[
ITAE = \int_0^T t|e(t)| \, dt \tag{5}
\]

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} e(t)^2 \tag{6}
\]
Where $e(t)$ is the output error at time $t$.

4. Design of the Optimisation Functions - Genetic Algorithms and Particle Swarm Optimisation

A. Genetic Algorithm.

As mentioned previously, GA algorithm aims to achieve the best solution in a population by revolutionizing individual within a number of iterations. Here is how GA is used to find the optimal PID values:

**Step 1 – Initialisation:**
Firstly, GA initializes a random population with a defined amount of individuals (solutions). Each solution carries a set of genes. Within the context of PID tuning, a set carries $K_P, K_I, K_D$ as genes.

**Step 2 – Evaluation:**
After that, GA assess the fitness/quality of each solution using the cost functions. Within the context of PID tuning, the gene set of an individual – $K_P, K_I, K_D$ – is updated in the real system. After that, the output speed of motor generates a certain amount of error. Refer to fig. 3, the error is then accumulated into the fitness value. The solutions with best fitness value have higher chance to be selected for mating process.

**Step 3 – Selection:**
Next, the breeding pairs from the population are chosen to generate new offspring – new solution and revolutionize the whole population. There are multiple methods to do this. Here, we choose to implement the most common method – *Roulette Wheel* method. To visualize, this method places all the solution on a wheel and spin it to randomly pick one, similar to how we play a Roulette wheel. The area that each solution occupies is proportional to their fitness value. Therefore, better individual possesses larger area on the wheel to get more chance to be picked [2].

**Step 4 – Crossover:**
After choosing breeding pairs, we go to crossover. This process is exchanging the genes of two parents to produces two offsprings – mating them. Within the context of PID tuning, GA simply swap/mix the $K_P, K_I, K_D$ values of two chosen solutions so that we have two new ones with different set of genes. We also have a parameter called “*crossover probability*” – how often the crossover is performed [3].

**Step 5 – Mutation:**
In order to avoid repetition, we also randomly tweak the gene set to ensure the diversity of the population and expand the search space. In mutation, we use “*mutation probability*”, to adjust the frequency of mutation process [4].

After that, the process goes back to step 2 and loop until one of termination conditions is met [5]:
- A defined fitness value is achieved.
- No major improvement within a number of iteration.
- The defined number of iteration is achieved.
- All of the above conditions are met at the same time.

The full process is shown on Figure 4.
B. Particle Swarm Optimisation

As mentioned previously, PSO algorithm searches for the optimum solution (particle) in a population by letting each one goes around their search space and report their best finding after each iteration. The movement of each solution in an iteration is defined by the following steps:

- The solution’s previous speed.
- The solution’s personal best known location – \( p_{best} \).
- The best known location of the swarm – \( g_{best} \).

Therefore, each solution moves toward \( p_{best} \) and \( g_{best} \) while maintaining its inertia. Because of that, it achieves a new speed in the next iteration, calculated with (7):

\[
v_i(t + 1) = w v_i(t) + c_1 r_1 [x_i(t) - x_i(t)] + c_2 r_2 [g(t) - x_i(t)]
\]

(7)

Where \( w \) is the inertia coefficient; acceleration constants \( c_1 \) and \( c_2 \) are cognitive and social parameter, respectively (\( 0 \leq c_1, c_2 \leq 2 \)); \( r_1 \) and \( r_2 \) are random numbers from 0 to 1, generated after every velocity update; \( v_i(t) \) is the particle’s current speed; \( x_i(t) \) is the particle’s current position; \( x_i(t) \) is \( p_{best} \) and \( g(t) \) is \( g_{best} \).

Also, the updated position of each particle is:

\[
x_i(t + 1) = x_i(t) + v_i(t + 1)
\]

(8)

The PSO optimisation can be presented with the following steps:

**Step 1 – Initialisation:**
Firstly, we creates a random population with a defined number of particles (potential solutions). Each solution includes a random position and speed.

**Step 2 – Evaluation:**
Then, PSO assesses quality of each solution using a performance index (cost function).

**Step 3 – Assigning \( p_{best} \) and \( g_{best} \):**
If the particle’s location is better than \( p_{best} \), then it will replace \( p_{best} \). After that, the best values of \( p_{best} \) is updated to \( g_{best} \).

**Step 4 – Update speed and position of the swarm:**
These updates can be calculated using functions from (7) and (8).

After step 4, the process goes back to step 2 and loop until the termination condition is met, similar to GA. The block diagram and the information flow of the PSO process are depicted in Figure 5.
As it can be seen from Figures 4 and 5, the GA and PSO have similar outcomes, but the optimization functions might differ, but the complexity of the processes is comparable.

5. Results of the Implementation
Table 3 shows the parameters, designed for GA optimization system.

Table 3. Parameter of GA.

| GA PARAMETERS | VALUE/METHOD |
|---------------|--------------|
| Population size | 60 |
| Number of generations | 80 |
| Bound values | \([0 0 0] – [500 500 500]\) |
| Fitness function | ITAE |
| Selection method | Roulette Wheel |
| Crossover method | Arithmetic Crossover |
| Crossover probability | 0.8 |
| Mutation method | Uniform Mutation |
| Mutation probability | 0.08 |

Using GA optimization, the following gains for PID controller were obtained: \(K_P = 493.4472, K_I = 489.2545\) and \(K_D = 499.9636\).

Table 4 shows the optimization parameters, utilised for PSO-based system.

Table 4. Parameters of PSO.

| PSO PARAMETERS | VALUE/METHOD |
|---------------|--------------|
| Population size | 60 |
| Number of generations | 80 |
| Bound values | \([0 0 0] – [500 500 500]\) |
| Fitness function | ITAE |
| Acceleration constant | 1.2 |
| \(c_1\) | 1.2 |
| \(c_2\) | 1.2 |

Using PSO optimization, the following gains were calculated for the given conditions: \(K_P = 45.2444, K_I = 495.8561\) and \(K_D = 3.9758\).
Applying the PID parameters to the adaptive PID controller for BLDC Motor (Fig.3), we deduced step responses for both systems, with GA and PSO. Fig 6 presents the step response for both control systems using the same plant model of BLDC motor.

![Step Response](image)

**Figure 6.** Step Response of the Developed Solution.

Table 5 presents the numerical values of the transient performance indicators, achieved using both systems in comparison with the derived requirements.

| Optimizer/Requirements | %OS | Tr (s)   | Ts (s)   |
|-------------------------|-----|----------|----------|
| GA                      | 0   | 8        | 1.5      |
| PSO                     | 0   | 0.0102   | 0.0182   |
| Requirements            | ≤ 2.5 | ≤ 0.005 | ≤ 0.01  |

The results can be analysed with the following conclusions. Firstly, both optimizing algorithms achieve perfect overshoot - 0% with no steady state error, as it is important for the steady-state performance evaluation. This outcome proves the superior performance in both speed and quality of using adaptive control compared to traditional methods. However, PSO failed to adapt both rise time and settling time requirements while GA not only succeeds on overcoming them, but also achieves exceptionally good results.

In particular, for rise time, PSO gets 0.0102 (s), which is equal to 210% of the requirement. The rise time of GA, on the other hand, is only to 1.6% of the requirement.

For settling time, Ts of PSO equals 185% of the requirement while it is only 0.82% for GA.

In conclusion, due to much superior performance, GA is selected to optimize PID parameters in our BLDC motor drivetrain for the future use due to its performance.

**6. Conclusion and Future Work.**

The paper presented the optimisation control algorithms design for the BLDC drivetrain of the electric bike. The model of the typical BLDC motor was developed to do the initial tuning of the system. Then, parameters of the function were deduced from the chosen motor type and the framework of the bike. Two optimizing algorithms for the controller were discussed: GA and PSO. Both systems showed no overshoot with zero steady state error. However, it is shown that GA has better overall performance indicators.
compared to the requirements. PSO, on the other hand, failed to adapt such requirements with larger values of the transient response parameters.

For the future work, we will apply more cost functions and adjust the parameters of PSO to achieve better step responses. In addition, we will do experiments to apply cloud computing for PID optimizer in order to save hardware cost with a reasonable performance. Finally, we will implement this system on the real prototype to justify the results.

References
[1] Kolbasov A, Karpukhin K, Terenchenko A, and Girutskiy O "Efficiency of photoelectric converters intellectual system application on ground electric transport," in IOP Conference Series: Materials Science and Engineering, 2019, p. 012011
[2] Kolbasov A, Karpukhin K, Terenchenko A, and Kavalchuk I "Concept of intellectual charging system for electrical and plug-in hybrid vehicles in Russian Federation," in IOP Conference Series: Materials Science and Engineering, 2018, p. 012013
[3] Cherry C and Cervero R "Use characteristics and mode choice behavior of electric bike users in China," Transport Policy, vol. 14, pp. 247-257, 2007
[4] Waide P and Brunner C U, "Energy-efficiency policy opportunities for electric motor-driven systems," 2011
[5] Sierens R, E. J. T.-A. S. o. M. E. J. o. E. f. G. T. Rosseel, and Power, "Variable composition hydrogen/natural gas mixtures for increased engine efficiency and decreased emissions," vol. 122, pp. 135-140, 2000
[6] Kavalchuk I, Seyedmahmoudian M, Horan B, Oo A T, and Stojcevski A, "Design and Control Algorithms for Power Electronic Converters for EV Applications," World Academy of Science, Engineering and Technology, International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering, vol. 9, pp. 1221-1226, 2015
[7] Pillay P and Krishnan R J. I. T. o. i. a., "Application characteristics of permanent magnet synchronous and brushless DC motors for servo drives," vol. 27, pp. 986-996, 1991.
[8] Iizuka K, Uzuhashi H, Kano M, Endo T, and Mohri K J. I. T. o. I. A., "Microcomputer control for sensorless brushless motor," pp. 595-601, 1985
[9] Uygun D and Solmaz S, "Design and dynamic study of a 6 kW external rotor permanent magnet Brushless DC motor for electric drivetrains," in 2015 IEEE 5th International Conference on Power Engineering, Energy and Electrical Drives (POWERENG), 2015, pp. 87-92.
[10] Kavalchuk I, Arisoy H, Oo A T, and Stojcevski A, "Challenges of electric power management in hybrid and electric vehicles," in Power Engineering Conference (AUPEC), 2014 Australasian Universities, 2014, pp. 1-7
[11] Hussain K M, Zepherin R A R, Kumar M S, and Kumar S M G, "Comparison of PID Controller Tuning Methods with Genetic Algorithm for FOPTD System," International Journal of Engineering Research and Applications vol. 4, pp. 308-314, 2014
[12] Mirjalili S, "Evolutionary Algorithms and Neural Networks: Theory and Applications," in Evolutionary Algorithms and Neural Networks vol. 780, J. Kacprzyk, Ed., 1 ed. Gewerbestrasse 11, 6330 Cham, Switzerland: Springer, Cham, 2018, pp. 43-55
[13] Zhao W, Lin Q, Shi Y, and Fang X "Mining the Role-Oriented Process Models Based on Genetic Algorithm," presented at the Advances in Swarm Intelligence, Shenzhen, China, 2012
[14] Namboothiripad M K and B. R., "International Journal of Emerging Technology and Advanced Engineering," International Journal of Emerging Technology and Advanced Engineering. vol. 2, pp. 310-314, 2012
[15] Wali M "PROPORTIONAL-INTEGRAL(PID) CONTROLLER DESIGN USING GENETIC ALGORITHM (GA)," Al-Qadisiya Journal For Engineering Sciences, vol. 4, pp. 75-92, 2011