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A new controller for energy management system of EV

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Abstract. Recent concerns about rising fuel prices and greenhouse gas emissions have focused attention on alternative energy sources, particularly in the transport sector. Transportation consumes 40% of overall fuel usage. As a result, a growing majority of researches on Electric Vehicles (EVs) and their Energy Management Systems (EMS) have been done. In order to enhance the performance and to meet the needs of drivers, more information regarding the EMS is needed. A new Energy Management System is proposed using a FOPID controller. To put the concept into practice, state equations are utilised. The fifth-order state-space model under study is a linked model with several inputs and outputs and the transfer matrices are calculated for decoupling the system. Utilizing these transfer matrices to decouple the system and FOPID controller is used to tune the system. The tuned parameters are minimized using a Particle Swarm Optimization (PSO) approach with Integral Time Absolute Error (ITAE) as the goal. When the suggested FOPID system's results are compared to those of PID-controlled systems, a sizable improvement is observed, which is explained by the results.

Keywords: energy management system; FOPID; PSO

1. Introduction

One of the most pressing issues confronting India today is energy scarcity. As a result, we're moving toward renewable energy sources that are both cost-effective and abundant in nature. For long-term energy sustainability, we must drastically reduce our reliance on fossil fuels. The use of renewable energy sources to generate electricity is quickly expanding around the world. In the renewable energy sector, India is one of the most rapidly developing countries. The Indian government is increasingly focusing on renewable energy sources for electricity generation (Husain and Shrivastava 2020, Javed *et al*. 2019, Javed *et al.* 2019).

The use of electric energy storage systems (EESS) to successfully approach active/ reactive current balancing, power grid frequencies management, production quality enhancement, voltage control, and other activities can help to boost renewable energy integration into the main power grid (Zhang *et al.* 2020).

EESS technology can smooth out the power output of sustainable energy producers like solar pv, biomass, geothermal, wind, waves, and hydroelectric power plants, as well as providing a conditionally dependable and distributed energy supply for power grids or local loads in general.

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Pumped water, compressed air, and flywheels are the three mechanical storage solutions available for EESS. SMES is a type of electrical storage. Chemical storage alternatives include pumps and flywheels (which includes batteries and fuel cells). The power ratings and charging / discharging speeds of EESS, as well as its power/energy density and lifespans, limit its real-world applications (Yang *et al.* 2020).

Batteries are one of the most efficient and high-energy storage devices available (Verma and Srivastava 2021). Renewable energy applications, on the other hand, are commonly subjected to several short-term charging/discharging cycles, limiting their service life. These operating pressures are particularly high since renewable energy applications are typically exposed to multiple short-term charging/discharging cycles. Furthermore, batteries have a hard time responding quickly to significant transient currents due to their low power density. On the other hand, in SMEs' storage systems increased power density, as well as a faster transient reaction time, a longer cycle life, and a lower self-discharge rate, are all advantages of power-type storage devices. There is a lack of energy density in SMEs' equipment, making it impossible to ensure a steady flow of electricity over time. Because of this, battery/SMES hybrid energy storage systems (BSM-HESS) had gained in popularity as a practical approach to combine the operational advantages of batteries and SMES systems, enabling great performance for a variety of energy storage demands. Electric trains, linear wave power converters, railway systems, electric vehicle rapid charging stations, and even photovoltaic-based microgrids are among them (Li *et al.* 2020). Contrarily, the construction of a BSM-control HESS system is more challenging than that of a single EESS system due to the need to take into consideration the varied properties of numerous energy storage devices. However, when power electronic devices are used, several factors emerge, including severe nonlinearities such as coupling and BSM-HESS modelling errors.

Energy management strategy (EMS), which includes both online and offline EMS, is frequently used to ensure the best power distribution across several EESS devices. RBS, FBS, and FLS are semi-empirical online approaches, whereas DP and Pontryagin's minimal principle are offline processes that apply global optimization methodologies. After constructing the BSM-HESS references, an EMS must establish a suitable underlying controller to successfully regulate them, as well as a significant increase in robustness (Jiang, Xu, Li, Hu & Ouyang 2019).

Because of its high reliability and structural flexibility, a basic linear control system like proportional-integral-derivative (PID) control is perhaps the most widely employed control technique for BSM-HESS. Because its control gains are determined by one-point linearization, it is unable to maintain globally consistent control performance when operating circumstances vary, and in extreme cases, due to incorrect control gains, the stability of the closed-loop system can possibly collapse. To deal with such a tough challenge, several novel control mechanisms have been proposed. The application of port-controlled Hamiltonian (PCH) model-based energy shaping (ES) control for BSM-HESS was also examined, which considerably improved the closed-loop system's control performance. The BSM-HESS features a novel droop control that balances charging/discharging priority and protects batteries from overcharging and rapid cycling. Within the effective working range of BSM-HESS, innovative synergistic management of firm voltage variations was also demonstrated employing SMEs and batteries with significant power/energy capabilities.

The BSM-HESS is a highly nonlinear system due to the wide range of modelling mistakes, the use of power converters, as well as the close connection of different components (López *et al.* 2021).

The authors want to demonstrate a unique technique for prolonging battery life span by employing BSM-HESS and NRFOC (nonlinear robust fractional-order control) in EV applications by first using RBS to offer a current reference for the battery through optimal power assignment.

Then, using a high-gain disturbance observer and the 5th averaged BSM-HESS model, a perturbation is created by integrating nonlinearities, parameter fluctuations, and nonlinear dynamics (HGPO).

Moreover, a fractional-order PID control strategy completely compensates for the estimate's disturbance, resulting in high resilience as well as improved transient responsiveness and smooth tracking. Because NRFOC only needs to monitor DC bus voltage and battery current, it doesn’t require an accurate BSM-HESS model. The control systems implementation viability is demonstrated by a broad set of case studies from a hardware-in-the-loop (HIL) research on the D Space platform.

The significance of electric vehicle EMS with fractional order proportional integral derivatives is emphasised in this paper. The fifth order system state space equation and its derivation are discussed in this study, as well as some basic facts concerning coupling and particle swarm optimization.

This is how the rest of the paper is laid out. Section 2 deals with relevant work, section 3 with the proposed technique, section 4 with the results, and section 5 with the conclusion.

2. Related work

For a completely active battery/supercapacitor HESS, a new L2-ARC approach based on passivity-based L2-gain adaptive robust control (L2-ARC) is proposed. Internal structural elements are used to build a port-controlled Hamiltonian model with dissipation for HESS, and IDA-PBC is constructed to recognise its underlying control with regulation power management. IDA-PBC is a passive controller with intercommunication and damping assignment. The study's author, however, is not interested in reducing time and placing the L2-ARC on a fully loaded HESS system (Ryalat & Laila 2018).

A nonlinear strong fractional order control (NRFOC) as well as a rule-based strategy (RBS) for successfully distributing power needs are being developed for an electric vehicle (EV) hybrid energy storage system. The D Spaces platform's practicality was demonstrated using a hardware-in-the-loop (HIL) test. To apply NRFOC, the author of this study did not employ a BSM-HESS for Electrical Automobiles (Carter *et al.* 2012).

In this review-based study, the author discusses the current breakthroughs in rule-based and optimization-based EMS and power system requirements, as well as their advantages and limits. Pontryagin's Minimum Principle (PMP) is a method that uses Markov theory to investigate the driver's intent and the procedure state identification of HEVs, optimising the power control platform in the event of a change in the actual operational issue by taking into account the impact of people, vehicles, and roads on the power supply system (Saib *et al*. 2017).

In this article, a hybrid power system for an electric car is built with a fuel cell stack and a Lithium-ion battery, and power converters for power transfer are simulated. To split the power generated by power sources, a better state machine technique is also being developed. The regulations are designed to avoid battery overcharging in high SOC and overdischarging in low SOC, as well as frequent charging and discharging in the usual SOC range, all while lowering hydrogen use. According to a MATLAB simulation, the upgraded state machine technique is more reliable, beneficial to the battery, and uses less hydrogen (meaning it is less expensive) than the original state machine strategy which is referenced earlier.

This study proposes energy usage and reliability models for a bus using fuel cells, batteries, and supercapacitors. 2D Dynamic Programming (DP) was created to reduce energy usage and system deterioration. We show that the mean square error is not always the most accurate indication of a problem's solution using a mathematical notion of proportionate integrative coproduct controllers based on 2D Pontryagin's Minimal Principle in real-time energy management (2DPMP) (Xu *et al*. 2013). The mathematical foundation of proportional integrative derivative controllers is used to calculate the system's optimal performance. A novel goal function created from a number of computational intelligence approaches can be used to optimise the gains of a PID controller. Some of the most common computational intelligence approaches can be used to tackle the problem (Mora *et al*. 2016).

To successfully regulate EV speed, the author provided a (FOPID) fuzzy fractional-order PID controller based on the (ACO) Ant Colony Optimization technique. The ACO technique can be used to update all controller settings as well as membership functions in real time. The suggested controller's speed tracking capabilities are tested in the MATLAB-Simulink environment using a new European driving cycle (NEDC). IOPID, FOPID, and ACO-based fuzzy integer-order PID (IOPID) controllers outperform currently existing controllers. This fuzzy-based controller could be transformed into an ANFIS (fuzzy inference + neural networks). Without expert knowledge, it is difficult to develop learning and adaptive capacities (George *et al*. 2021).

3. Methodology

The importance of electric vehicle EMS with fractional order proportional integral derivatives is highlighted in this study. This paper discusses the fifth order system state space equation and its derivation, as well as some basic facts about coupling and particle swarm optimization.

3.1 System modeling

Fifth order system state-space equation and its derivation
Define the state vector as

$$r = (r_1, r_2, r_3, r_4, r_5)^T = (s_1, s_2, i_1, i_2, s_0)^T \tag{1}$$

Output $$p = (p1, p2)^T = (i_1, s_0)^T \tag{2}$$

Control input $$l = (l_1, l_2)^T = (D_1, D_2)^T \tag{3}$$

Tracking error $$e = [e_1, e_2]^T = [i_1 - i_1^*, s_0 - s_0^*]^T \tag{4}$$

You'll obtain the following result if you separate the path loss e from the express control input *u*

$$\begin{cases} \dot{e}_1 = \dfrac{v_1}{L_1} + \left(\dfrac{R_{on2} - R_{on1}}{L_1} D_1 - \dfrac{R_{L_1} + R_{on2}}{L_1} \right) i_1 + (D_1 - 1)\dfrac{v_0}{L_1} - \dot{i}_1^* \\ \dot{e}_2 = (1 - D_1)\dfrac{i_1}{C_0} + (1 - D_2)\dfrac{i_2}{C_0} - \dfrac{v_0}{RC_0} - \dot{v}_0^* \end{cases} \tag{5}$$

$$\begin{bmatrix} \dot{v}_1 \\ \dot{v}_2 \\ \dot{i}_1 \\ \dot{i}_2 \\ \dot{v}_0 \end{bmatrix} = \begin{bmatrix} -\dfrac{v_1}{R_e C_1} - \dfrac{i_1}{C_1} + \dfrac{E}{R_e C_1} \\ \dfrac{I_{SC} - i_2}{C_2} \\ \dfrac{v_1 - v_0}{L_1} - \left(\dfrac{R_{L_1} + R_{on_2}}{L_1} \right) i_1 \\ \dfrac{v_2}{L_2} + \left(\dfrac{R_{on_4} - R_{on_3}}{L_2} D_2 - \dfrac{R_{L_2} - R_{on_4}}{L_2} \right) i_2 + (D_2 - 1)\dfrac{v_0}{L_2} \\ (1 - D_1)\dfrac{i_1}{C_0} - \dfrac{v_0}{RC_0} + \dfrac{i_2}{C_0} \end{bmatrix} + \begin{bmatrix} 00 \\ 00 \\ \dfrac{R_{on_2} - R_{on_1}}{L_1} i_1 + \dfrac{v_0}{L_1} 0 \\ 00 \\ 0 - \dfrac{i_2}{C_0} \end{bmatrix} \begin{bmatrix} D_1 \\ D_2 \end{bmatrix} \tag{6}$$

As illustrated by the state space equation above, the system is a multi-input multi output coupled system. We estimated the transfer matrix from the state-space model to decouple the state-space model. This transfer matrix is used to achieve decoupling (George *et al.* 2021).

3.2 Decoupling

To gain a better understanding of disturbance decoupling The transfer function system is examined here.

$$\Sigma\begin{cases} z = Ad + Bu, \\ y = Cd + Du, \end{cases} \tag{7}$$

In all four appropriate rational matrices, disturbance (*d*), control (*u*), output (*z*), and measurement are included (*y*). All four of these properties are also present in the proper rational matrices (as shown in the preceding list) as well as in the strictly proper rational matrices (*D*).

The measurement feedback may be used to regulate the system (also called compensator)

$$l = Cp,$$

Using C as an appropriate rational matrix, we may create a closed-loop computer with such a transfer matrix.

$$A + B(1 - CD)^{-1}CC \tag{8}$$

If we refer to the input from the measurements as $\sum$

Are there compensators that can be used to make the transfer matrix in a closed-loop system equal to zero if *C* is a valid rational matrix, (George *et al.* 2020) i.e.

$$A + B(I - CD)^{-1}CC = 0 \tag{9}$$

And then calculate the highest matching order in *G* from *U* to *Z* say *r*.
Now, calculate the highest matching order in *G* from *D* to *Y*, say *q*.
And calculate the min-weight of an order *r* matching in *G* from *U* to Z, say $\mu.$.
Finally, calculate the min weight of a matching order *q* in *G* from *D* to *Y*, let's say *v*.

3.3 Computations

Firstly, calculate the maxorder of a matching from $U \cup D$ to *Z* in *G*, let's say r'

And calculate the maxorder of a matching from *D* to $Y \cup Z$ in *G*, now say q'

And then recall that whether *r* and *q* are equal to the generic ranks of *L* and *M* respectively. It is therefore obvious that r' and q' are equal to the generic rankings of $[A, B]$ and $\begin{bmatrix} A \\ C \end{bmatrix}$, respectively. It can be seen that if $X < X'$or $Y < Y'$ the DDPM cannot be solved generally, so we can stop examining its solvability at this point.

Now, calculate a size-X that corresponds from *U* to *Z* with a weight of $\mu.$. Consider that $u_1, u_2, \ldots\ldots, u_r$ and $t_1, t_2, \ldots\ldots, t_r$ have matching linkages. Denote by $B'$the square matrix made up of the first *r* rows and columns of B (Karki *et al*. 2020).

Calculate a weight of *v* and a size- *q* matching from *D* to *Y*. Let us suppose that the links that are matching $d_1, d_2, \ldots d_q$ to $p_1, p_2, \ldots p_q$. The square matrix comprised of the first *q* rows and *M* columns is denoted by M'.

Both identify and represent a matrix with rows and columns at its beginning. The DDPM solution for this particular system is only universally solvable when the initial system with transference matrices K, L, M, and N is solvable.

After decoupling the state-space model, a FOPID controller is used for tuning purpose. The R_p, R_i, R, λ and μ are pieces of gains that work to correct or reduce the error.

In order to achieve ITAE, a particle swarm optimization technique is used (Integral time absolute error). The formula of the ITAE is given below.

$$ITAE = \int_0^{t_s} |err| * t \tag{10}$$

Where,
$err \rightarrow$ Error
$t \rightarrow$ Time
$t_s \rightarrow$ Simulation time

3.4 Particle swarm optimization

Particle swarm optimization (PSO) is indeed a simple bio-inspired approach for determining the optimum solution in a solution space (Husain and Shrivastava 2020). It is distinguished from other optimization techniques either by fact that it just requires the objective function and is unaffected by gradients or distinguishable forms (Hossain *et al*. 2022).

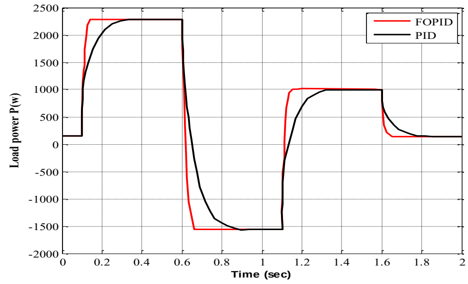
Computational science problems may be solved using a computer-aided approach called particle swarm optimization, in which candidates are continually improved on quality metrics. It uses a basic mathematical formula based just on particle's location and velocity to remedy a problem by creating a population of alternative solutions, which are referred to as "nanoparticles" in this context. The best-known site in each particle's local proximity influences its course, but it is also guided toward the best-known sites in the search space, which also are updated as better regions are discovered by other particles. As a consequence, the swarm's attention should be focused on the most effective options.

There are few, if there are any, assumptions the about problem at hand by PSO, which makes it a metaheuristic (Lu and Zhang 2022).

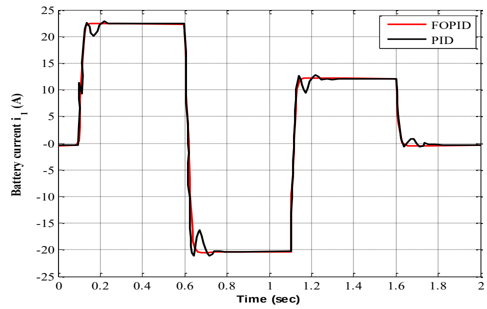
Like the PSO, Traditional optimization methods such as linear regression and semi methods don't need a differentiable optimization issue since they don't employ the problem's gradient. PSO, on the other hand, does not guarantee that the best solution will be discovered.

To avoid divergence, the inertia weight must be less than one. Using the constriction approach, the two additional parameters may be computed or freely selected, albeit the study suggests convergence places to confine them.

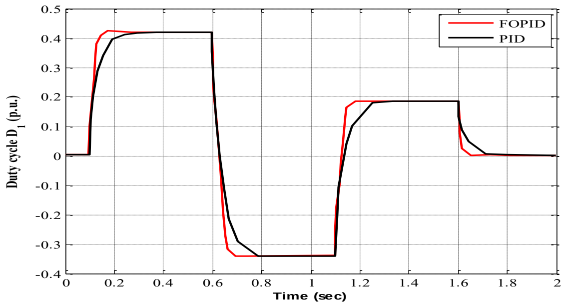
Swarm-based stochastic optimization, PSO, is used to find the best solution. For the purpose of re-creating their social behaviour, insects, mammals, birds, and fish all employ the PSO algorithm. These swarms use a cooperative food-finding technique, with each member of the swarm modifying the search pattern based on their own and others' learning experiences (Zhou *et al*. 2021).



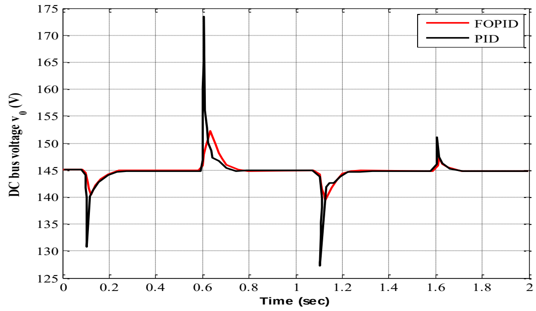
(a) Load response using FOPID and PID controller



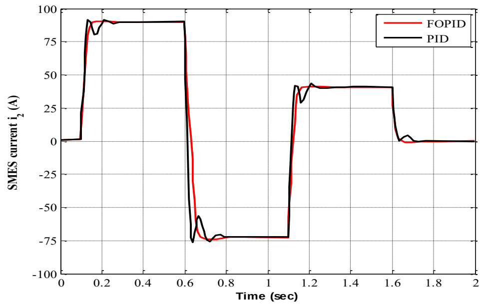
(b) Battery current regulation using FOPID and PID controller



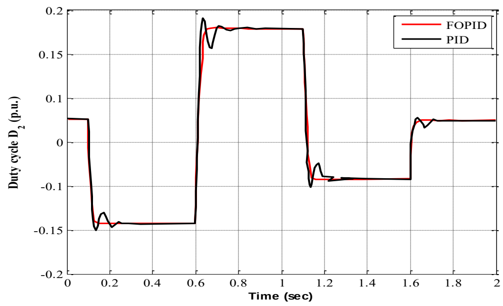
(c) Duty cycle – time response of FOPID and PID controller



(d) Variation of DC bus voltage with time of FOPID and PID controller



(e) SMES current vs time response of FOPID and PID controller



(f) FOPID rise time overshoot analysis

Fig. 1 Comparison of FOPID and PID controller

4. Results

From the Fig. 1(a) given below it is observable that the FOPID controller rapidly regulates the load power to its reference point, compared to PID controller. The rise time, overshoot and settling time of the FOPID controller are 0.12, 0 and 0.185. The rise time, overshoot and settling time of the PID controller are 0.16, 0 and 0.32.

From the Fig. 1(b) given below it is observable that the FOPID controller rapidly regulates the battery current to its reference point, compared to PID controller. The rise time, overshoot and settling time of the FOPID controller are 0.11, 0 and 0.15. The rise time, overshoot and settling time of the PID controller are 0.13, 0 and 0.23.

From the Fig. 1(c) given above it is observable that the FOPID controller rapidly regulates the duty cycle to its reference point, compared to PID controller. The rise time, overshoot and settling time of the FOPID controller are 0.13, 0 and 0.18. The rise time, overshoot and settling time of the PID controller are 0.155, 0 and 0.36.

From the Fig. 1(d) it is observable that the FOPID controller rapidly regulates the DC bus voltage to its reference point, compared to PID controller. The rise time, overshoot and settling time of the FOPID controller are 0, 0 and 0.26. The rise time, overshoot and settling time of the PID controller are 0, 0 and 0.28.

From the Fig. 1 (e) given above it is observable that the FOPID controller rapidly regulates the SMES current to its reference point, compared to PID controller. The rise time, overshoot and settling time of the FOPID controller are 0.11, 0 and 0.2. The rise time, overshoot and settling time of the PID controller are 0.134, 1.2% and 0.28.

From the Fig. 1(f) given above it is observable that the rise time, overshoot and settling time of the FOPID controller are 0, 0 and 0.68. The rise time, overshoot and settling time of the PID controller are 0, 2.1% and 0.85.

5. Conclusions

A (FOPID) Fractional-Order Proportional Integral Derivative controller is employed in this study to create an Energy Management System (EMS) of EV. State-space equations are used to put the concept into practice. A connected multi-input multi-output system used is the fifth-order state-space model. A transfer matrix for decoupling the system is created using the state-space model, and then these transfer matrices are used to decouple and optimise the system with the FOPID controller. With (ITAE) Integral Time Absolute Error as the target, the tuned parameters are minimised using a (PSO) Particle Swarm Optimization technique. The transfer matrices and state-space models are described separately. The tuning parameters are presented in the outcome section, along with the model's replies. Using the analysis of load response, battery current regulation, variation of DC bus voltage and SMES current, FOPID controller is found much better in comparison with PID controller.

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