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Result-Adaptive PID Control Based Ant Colony Optimization Tuning for Battery Operation Control in Standalone PV System With Consumption Side Power Management

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ABSTRACT

The evolution of the management of smart grids, which mainly aims to integrate various high-capacity energy sources, more specifically photovoltaic units, on the one hand, as well as optimal control of loads connected to the network in order to ensure coordination between production and consumption, leads not only to the management of production units but also to the management of consumption power using different static converters. This makes this operation possible, and feasible but complex because of their effects on the quality of energy and the need for reliable control. There are currently many studies focusing on power management from the consumption side. This article then proposes a new controller for managing the requested power by combining an optimization technique, which is the Ant Colony Optimization (ACO), with an adaptive PI regulator, which is the Result-Adaptive PID (RAPID) Control, as the controller of the operation of the battery. The battery represents an essential part in solar installations, enabling energy-efficient operation of the network by regulating the operation of controllable loads. To adjust the RAPID regulator using the ACO algorithm, we used an objective function to minimize the error between the input and output of the new regulator. Demonstrated on an isolated DC-AC network, the performance of the proposed controller for energy management on the consumption side is established after comparison with standard controllers such as the classic PI based trial & error methods and the RAPID tuned by ACO.

***Index Terms*—**Ant Colony Optimization (ACO), battery control, consumption side, Result-Adaptive PID (RAPID), standalone PV system

I. INTRODUCTION

A. Inspiring

Historically, power grids were initially envisioned as centralized systems, supplying vast geographical areas from large power plants. However, with the emergence of microgrids, distributed generation units, and distributed renewable energy sources, the energy landscape is shifting towards a more distributed and flexible structure. Microgrids are autonomous entities capable of operating in connection with or in isolation from the main grid, giving them greater resilience in the event of failure or natural disaster. Alongside this, the integration of low-voltage DC-AC and AC-DC power technologies has become crucial to optimizing network efficiency and enabling better management of energy generation, storage, and distribution. This evolution towards connected and isolated power grids, combined with the growing adoption of innovative technologies, paves the way for a more flexible, robust, and sustainable energy infrastructure [1-3].

The integration of photovoltaic (PV) systems with batteries constitutes a major advance in the field of energy production and management. These systems can be deployed as stand-alone microgrids or connected to the main grid, offering greater flexibility in energy management. In a stand-alone context, battery-powered photovoltaic systems can provide a continuous power supply in isolated or remote areas, where access to the traditional electricity grid is limited or non-existent. These stand-alone microgrids offer a sustainable solution for meeting local energy needs while reducing dependence on fossil fuels. This approach ensures more efficient use of renewable resources and promotes the harmonious integration of clean energies into the overall energy mix [4-6].

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The importance of energy management in battery photovoltaic systems can hardly be overstated. The management approach uses various modes and procedures to optimize system efficiency and reliability. Modes include charging, discharging, voltage control, and bidirectional flow management between solar panels, batteries, and the grid. Static converters are essential to ensure efficient conversion between different system voltages and currents, enabling these processes [7-10].

Furthermore, the creation of sophisticated controllers is necessary to precisely and responsively monitor and control energy flows. These controllers maximize system performance while maintaining stability and security by adjusting operating settings in real time using complex algorithms and optimization techniques. By utilizing optimization techniques, controller gains can be adjusted in response to changes in load, meteorological conditions, and other system attributes, ensuring optimal energy management under all circumstances. In conclusion, to ensure the dependable, sustainable, and financially feasible operation of these micro-energy networks, energy management of battery PV systems necessitates an integrated and proactive approach combining sophisticated control techniques, efficient static converters, and adaptive optimization methodologies [11, 12].

Additionally, the management strategy ensures a steady and dependable energy supply while maximizing the autonomy of the system and optimizing the use of available resources. Therefore, a key component of the shift to a sustainable and resilient energy future is holistic energy management, which includes energy production, storage, and consumption [13].

Numerous research studies have explored and proposed innovative methods for consumer-side energy management in PV-battery systems. For example, in their paper entitled "Artificial intelligent control of energy management PV system," Takialddin et al. [14] presented an artificial intelligence-based approach to optimizing load management, enabling dynamic adaptation in response to changing system conditions.

Moreover, the evolution of PID controllers towards adaptive controllers has considerably improved consumer-side energy management in battery-powered photovoltaic systems. Adaptive controllers incorporate mechanisms for automatically adjusting controller parameters to variations in operating conditions, resulting in a more dynamic and accurate response to system disturbances. This development has been largely supported by innovative research exploring the use of optimization methods such as genetic algorithms (GA), particle swarm optimization (PSO), and Gray Wolf algorithm optimization (GWO), among others, to determine optimal PID controller gains. For example, in their paper "Genetic Algorithm-Optimized PID Controller for Better Performance of PV System," Roshdy et al. [15] proposed a method based on genetic algorithms to determine optimal PID controller parameters, thus ensuring efficient control with maximum performance. Similarly, many studies on particle swarm optimization applications for tuning the PID controller have shown how effective optimization techniques are at enhancing PID controller performance in battery PV systems, guaranteeing accurate regulation and dynamic stability under a range of operating circumstances. These developments highlight the increasing significance of control and optimization research in battery-powered photovoltaic microgrids.

B. Existing research limitations

By evaluating the studies mentioned above, we can clearly mark the positive results obtained and the improvements made to power management on the consumption side. However, this existing research shows limitations such as most research work on energy management controllers uses the classic PID regulator by calculating the gains either by trial and error, by classic methods, or by classic methods or optimizing these gains through optimization methods. However, even if we find adaptive PID regulators, the latter are not really validated. Consequently, any simulation results obtained by these types of adaptive regulators make these analyses unsuitable for real-time application.

C. Research contributions

Based on the shortcomings of the above-mentioned works, this paper proposes a new consumer-side power-saving management regulator for DC-AC standalone networks by merging the adaptation of the classic PID regulator (i.e., a PID with adaptive gains) with the ACO method to minimize error and improve optimization of gains. This technique offers double regulator adjustment. The adaptive regulator proposed here is validated practically, as we will see in the following sections, and is capable of determining optimal decisions in real-time. Finally, the metaheuristic technique chosen in this article is known for its effectiveness in different applications requiring optimization.

II. CONSUMPTION DEMAND SIDE MANAGEMENT AND ASSOCIATED CHALLENGES

Consumption-side power management refers to the management of electricity demand by end users. It aims to optimize energy consumption according to the needs and constraints of the electricity network. This approach helps reduce costs, improve energy efficiency, and promote the integration of renewable energies. The challenges related to power management on the consumer side are numerous. They include, in particular [16-20]:

- The variability of electricity demand depending on the time of day, days of the week, and seasons.
- The need to effectively coordinate and control end-user electrical devices to meet network needs.
- The engagement and active participation of end users in the management of their energy consumption.

Much research has been carried out in the field of consumption-side power management, more precisely in the case of an isolated solar station. This work aims to develop methods and technologies to optimize the energy consumption of end users. For example, in [21] where the study focuses on the demand side management in a PV system integrated with a greenhouse. This work investigates the starting time of incoming power, maximizes power generation, proposes the use of the PSO algorithm, and analyses the greenhouse production activities. Another significant study was presented in [22], with a new strategy proposed and tested in real-time under stochastic electricity consumption; the authors of the mentioned paper analyze the behavior of the strategy on stand-alone PV systems.

Consumption-side power management is closely linked to intelligent networks, also called "smart grids" [23]. Smart grids integrate information and communication technologies into the electricity grid to enable more efficient and flexible management of electricity production, distribution, and consumption [24, 25]. They facilitate the implementation of consumption-side power management by enabling two-way communication between end users and the power grid. This allows end users to receive real-time electricity price information and make informed decisions about their energy consumption. Additionally, smart grids enable grid managers to control and manage electricity demand more precisely and efficiently.

In the context of consumption-side power management for a photovoltaic (PV) installation, some of the commonly considered objective functions are:

- Minimization of energy consumption from the electrical network to maximize self-consumption of solar energy produced by the PV installation, reducing dependence on the electricity grid and promoting the use of renewable energies [26].
- Minimizing electricity costs by adjusting energy consumption based on price signals [24, 25, 27].

III. PROBLEM STATEMENT OF BATTERY CONTROL IN PV INSTALLATIONS IN COORDINATION WITH CONSUMPTION-SIDE POWER MANAGEMENT

The battery control problem in photovoltaic (PV) installations, in coordination with consumption-side power management, aims to optimize battery usage based on energy consumption needs and power grid constraints. The objective is to find effective control strategies to maximize the self-consumption of solar energy produced by the PV installation, minimize electricity costs, and ensure the stability of the system. Several research works have focused on battery control in PV installations. Some of these works have concentrated on the use of PID (Proportional Integral Derivative) regulators for battery control. For example, in [28], the authors applied some heuristic methods for tuning the PID controller of a hybrid battery/supercapacitor system, such as the LMI Method, GA, and other, authors focused solely on mange of the HESS power. In another study presented in [29], the author changed the classical PID controller with the Fractional Order PID in a new type of inverter. The results have shown the effectiveness of the proposed method. Additionally, the authors in [30] aimed to work on the PV system with the superconducting magnetic energy storage system, where the controller proposed for this system was the PID tuned by fuzzy rules.

For high and effective injection of PV power to the grid, this paper [31], presents a new design and implementation of a robust PID regulator based on an Artificial Neural Network (ANN-PID).

Isolated or autonomous solar systems are also studied in several articles [32, 33] where the PID regulator of the DC-DC converter in this study is based on different techniques such as the Hybrid Whale Optimization Algorithm in [32].

All these articles provide detailed information on battery control approaches in PV installations using classical PID controllers based on heuristic methods and metaheuristic methods. But this entire work uses just the classical PID and tunes its gains.

Based on the related battery control in a PV system, we can distinguish several problems, including:

- Poor control of battery charging and discharging can lead to premature battery degradation and reduced battery life.
- Complete loss of control of the battery, which can result in overcharging or over-discharging the battery, potentially damaging the PV system and compromising the stability of the power grid.
- Owner management issues, such as voltage and frequency fluctuations, are due to inadequate battery control.

For that, it is essential to implement robust and reliable control strategies to avoid these problems and ensure the optimal operation of the PV system.

IV. RAPID CONTROL OF BATTERY SYSTEM

Result-adaptive PID control (RAPID control), originally developed for position control of laser scanners by M. Lugmair et al. [34], has shown significant performance improvements through experimental validation and has gained popularity thanks to its ability to dynamically adjust control parameters. Building on these positive results, RAPID control is now being considered for improving energy management in smart grids. This decision is supported by substantial experimental results from the application of the laser scanner, which indicate its potential to optimize energy management in smart grids by offering greater precision and adaptability.

As shown in Fig. 1, the RAPID controller can be utilized with adaptive scaling factors, where the input signal of the RAPID regulator is the voltage bus, while the output is the battery reference current. Then, the conventional PID is employed to control the current error and generate the desired duty cycle.

The continuous-time equivalent expression for the PID regulator can be written as:

$$G(s)=K_p e(t)+\frac{K_i}{T_i}\int_0^t e(t)dt+K_d T_d\frac{de(t)}{dt} \tag{1}$$

where: (s): the control function, $e(t)$: the error function (set point - measurement),

K_p: Proportional gain, K_i: Integral gain, K_d: Derivative gain, and T_i: Constant time.

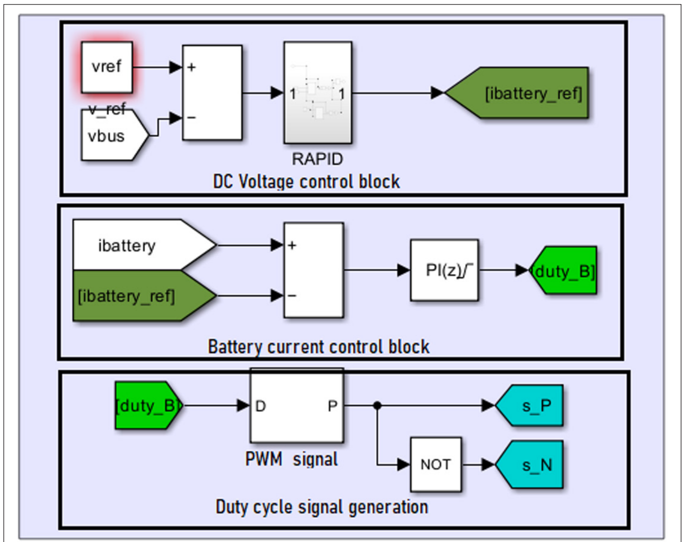

Fig. 1. Battery control configuration.

The dynamic behavior of photovoltaic systems under different conditions requires the use of improved control strategies. This means that the PID battery controller described above cannot adequately handle the process under various operating conditions. Therefore, the tuning of the PID controller is crucial.

This function (1) can be written in the Laplace domain as follows:

$$G(s)=K_p\left(1+\frac{1}{ST_i}+T_dS\right)e(s) \quad (2)$$

where the control function U(s) is:

$$U(s)=K_p\left(1+\frac{1}{ST_i}+T_dS\right) \quad (3)$$

In practice, the derived effects are usually filtered using a first-order low-pass filter with a time constant to avoid over-sensitivity to measurement noise and set-point edges.

A. Proportional term Adaptation in RAPID Regulator
The over-amplification may cause overshoot and oscillation. P-adaptive solves this problem by continuously changing the proportional gain based on the current error value. This adjustment ensures that the gain is higher for smaller errors, thus promoting faster convergence, while for larger errors, the gain is reduced to prevent overshoot. The adaptation function controlled by parameters c1 and c2 determines the behavior of this adaptation. By fine-tuning these parameters, the control system can optimize performance, achieving high accuracy and minimal overshoot. The adaptive function of the proportional term is given by:

$$f_p(e)=1+\frac{c_1-1}{(c_2e)^2+1} \quad (4)$$

This feature has two parameters, c1 and c2, that must be properly aligned to optimize control. For different values of the error function e, c1 determines the value of the function at $e=0$, while c2 determines the slope of the function. For large error values, the functional value equals 1 (meaning the P value is not increased), and for small values of e, the functional value becomes c1 (indicating that the P value is increased by a factor c1).

B. Integral term Adaption
I-adaptation solves the problem of slowing down the response of the system by selectively activating the integral only for sufficiently small error values. This is achieved through a continuous adaptive function that controls the behavior of the integral components. Parameter c1 determines the slope of the function and affects when integration is activated. During the transient phase, the adaptive function inhibits integration to prevent overshoot. Once the error becomes smaller, the integral gradually increases, effectively reducing the residual error without causing an overshoot. The adaptive function of the proportional term is given by:

$$f_i(e)=\frac{1}{(c_1e)^2+1} \quad (5)$$

Only one parameter, c1, must be defined, determining the slope of the function. For large values of e, the functional value approaches zero, and for small errors, it approaches one. The integral part of the command is multiplied by the functional value of the left adaptive function. Thus, the integrator input is set to zero during stabilization (when the error value is large), and only after the error value becomes small (post-stabilization) does the integrator input open. Integration of e and error reduction only begins after the stabilization phase, preventing overshoot.

V. ACO-RAPID CONTROLLER

This section describes the use of an ant colony algorithm to adjust the RAPID parameters.

A. Review of Ant Colony Optimization Methods
Ant Colony Optimization (ACO) algorithm is a class of algorithms that are inspired by the behavior of ants and their ability to find optimal paths between a food source and the anthill (Fig. 2 and 3). These algorithms are specially designed to solve discrete optimization problems. Some of the major problems addressed in the literature

Fig. 2. Path of a set of ants.

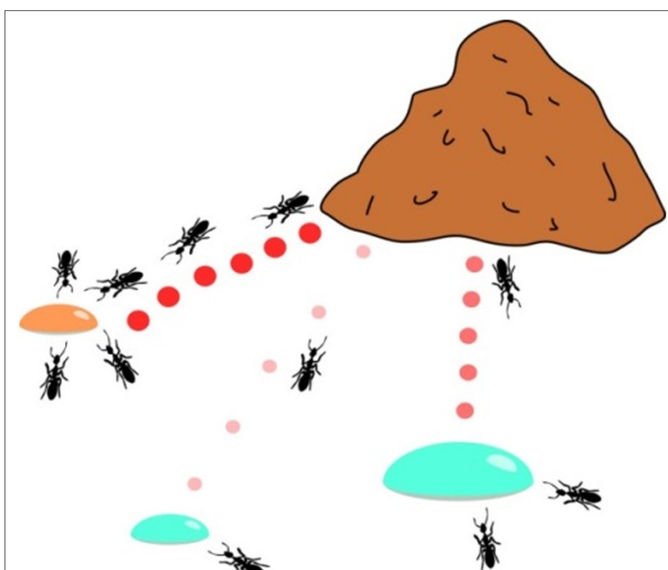

Fig. 3. Ants path process.

with ACO algorithms include the Traveling Salesman Problem, network routing, and sequential ordering.

In recent years, most research on ACO algorithms has focused on improving the underlying algorithms. Among the most successful variants are the Elitist Ant System [35], Rank-Based Ant System [36], Max-Min Ant System, and Hypercube Framework [37].

B. Formulation of the Ant Colony Optimization Problem

The ACO algorithms [38] provide solutions to discrete optimization problems inspired by the observation of food consumption behavior of human colonies. Although some authors have developed versions of the ACO algorithms for continuous optimization, not many studies have been carried out in this direction and, therefore, the focus of the discussion that will be presented here will center on discrete optimization.

Assuming a connected function f = (*x*, *y*) represented by a graph, the basic ACO algorithm can be used to find a solution to the shortest route problem defined in the graph [38]. One solution is a route in the function that connects an origin node 'a' with a fate node 'b', and the length of the route is determined by the number of arcs crossed.

Associated with each edge (*i*, *j*) of the graph, there is a variable τ_{ij} called an artificial pheromone ring, or simply pheromone. Each artificial ant is capable of "designing" an arc with a pheromone and "feeling" (reading) the pheromone on the bow. Each node 'a' passes through a node 'b' in each iteration, and in each node 'a', the local information on the level of pheromone, τ_{ij}, is used by the device in a way that can decide in a probabilistic manner the next node to which to unfold, based on the following rule:

$$p_{ij}^{k}(\begin{cases} \dfrac{\tau_{ij}(t)}{\sum_{j \ni Ni} \tau_{ij}(t)} \text{se } j \in N_i \\ 0 \text{otherwise} \end{cases} \tag{6}$$

The probability that ant *k*, located at position *i*, moves to position *j* at iteration *t* is denoted as $p^k_{ij}(t)$. The pheromone level of edge (*i*, *j*) is denoted as $\tau_{ij}(t)$, both taken at iteration *t*. *Ni* represents the set of neighbors of position *i*.

During the path of an arc (*i*, *j*), the ant deposits pheromone on it, and the pheromone level of the arc (*i*, *j*) is updated according to the following rule:

$$\tau_{ij}(t) \leftarrow (1-\rho)\tau_{ij}(t) + \Delta\tau \tag{7}$$

where *t* is the iteration counter, τ is the constant amount of pheromone deposited by the ant, Δτ is the variation of pheromone in the arc (*i*, *j*), and ρ ∈ (0, 1] is the decay rate of the pheromone.

An ACO algorithm alternates, for a maximum number of iterations, the application of two basic procedures:

1. A parallel solution construction/modification procedure in which a set of N ants constructs/modifies N solutions in parallel for the problem under consideration.
2. A pheromone-on-traces update procedure, in which the amount of pheromone on the traces of the edges of the problem graph is changed.

The process of building or modifying a solution occurs probabilistically, and the probability that a new edge is added to the solution under construction is a function of the heuristic desirability of the edge η and the pheromone τ deposited by the previous ants. The desirability heuristic η expresses the probability that an ant will move on a given arc. For example, in case one is looking for the shortest path between a number of edges, the desirability η is usually chosen as the inverse of the distance between a pair of nodes [38].

The ACO algorithm can be summarized in the following steps:

1. Initialization: Set initial pheromone levels on all edges.
2. Construction of Ant Solutions: Each ant constructs a solution to the problem (a path through the graph) by moving from vertex to vertex along the edges, choosing the next vertex based on a probabilistic rule.
3. Pheromone Update: After all ants have constructed their solutions, update the pheromone levels on the edges. This is typically done by decreasing (evaporating) all pheromone values and then increasing them based on the quality of the ant solutions (shorter paths get higher pheromone increases).
4. Termination Check: If a termination condition is met (such as a maximum number of iterations or a satisfactory solution has been found), stop the algorithm. Otherwise, go back to Step 2.

The probabilistic rule used by the ants to choose the next vertex typically takes into account both the amount of pheromone on the edges and the distance to the next vertex. This rule balances exploration (choosing edges with low pheromone levels) and exploitation (choosing short edges).

In our case, we adopted the integral time absolute error function to minimize the error at the input of the PI regulators [39], this function is represented by the following equation (8):

$$ITAE = \int_0^\infty t\left|e(t)\right|dt \tag{8}$$

VI. SIMULATED SYSTEM

For testing the performance of the adopted control strategy, which is the RAPID controller based on the ACO method, a standalone PV system with a battery and load is simulated, as shown in Fig. 4. The specific parameters are mentioned in Table I. Note that the boost converter of the PV system is based on the P&O MPPT strategies.

The simulation was done in two steps: firstly, we compare the obtained results between the classical PI controller based on the error and trial technique with the only RAPID controller without optimization.

Whereas in the second step, we compare the obtained result using the RAPID controller with and without ACO to demonstrate the effect of the optimal gain.

VII. RESULTS AND DISCUSSION

A. Classical PI Vs RAPID controller

Table II shows the P and I gain using the controller. The gain in the case of the RAPID controller is generated by the controller itself, and we remark the two gains are the same.

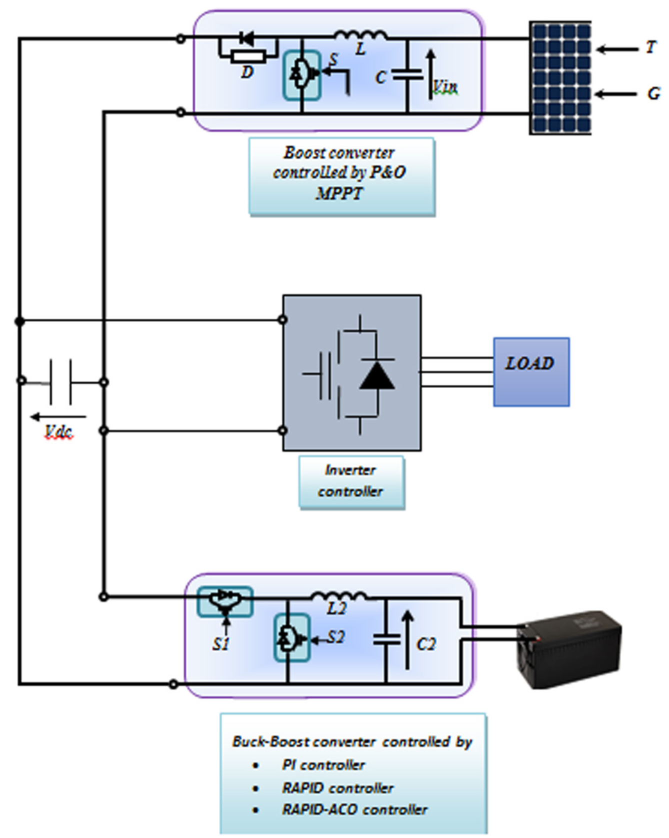

Fig. 4. Studied system.

TABLE I. STUDIED SYSTEM PARAMETERS

	Solartrch renewables STR215	
PV Module	Maximum power (W)	214.963
	Open circuit volatgeVoc (V)	36
	Short-ciruitcurantIsc (A)	7.73
	Voltage at maximum power point Vmp (V)	28.7
	Current at maximum power point Imp (A)	7.49
	Shunt resistance Rsh (ohms)	5284.6435
	Series resistance Rs (ohms)	0.36886
Battery	**Lithium – Ion**	
	Nominal voltage (V)	24
	Rated capacity (Ah)	50
	Initial state of charge (%)	45
Charge DC	R (ohms)	5
Charge AC	Nominal voltage (V)	2200
	Frequency (Hz)	50
	Active power (W)	3000
	Reactive power (Var)	300

TABLE II. REGULATOR GAINS

	Kp	Ki
PI Classical	10	100
RAPID	0.5527	0.5527

In this case, we fix the sunshine for the PV at G = 300 W/m^2. Fig. 5 shows the output characteristics of the PV panel which are respectively: PV voltage, Vdc voltage, PV current, and PV power.

Fig. 6, 7, and 8 shown respectively the Vdc battery side, the battery voltage, and its current.

Based on Vdc behavior described in Fig. 6, we can clearly show that the response of RAPID performs better than the classical PI controller, especially in terms of response time and overshoot.

This remark can be confirmed using the results shown in Fig. 7 and 8. In these two figures we can see clearly that RAPID gives more stability to the battery compared to the classical PI based on error & trial technic.

Table III summarizes the obtained results using the PI and RAPID Controllers. In this table, we can see that the Adaptive PI control allowed us to improve response time and minimize overshoot.

So compared to the classical PI controller based on trial & error technic, the resulting adaptive PI controller offers improved performance, especially in terms of response time.

B. RAPID Vs ACO-RAPID controller

The simulation is run on an Intel(R) Xeon(R) W-2102 CPU 2.90 GHz with 16 Go RAM, the following parameter values for ACO of PID, as shown in Table IV.

Fig. 9 confirms the convergence of the ACO method, which aims to minimize the error, as we presented the minimization of error by the ISE-type objective function.

After convergence, Table V summarized the parameter values of RAPID and RAPID with ACO algorithm.

As the first step, to demonstrate the effect of the ACO on the enhancement of the RAPID regulator, we perform a comparison between the two cases: only the RAPID imposes the P and I adjustment gains, and the ACO optimizes this gain and proposes other optimal gains.

Note that in this step, we use a variable sunshine for the PV panel to make the system more dynamic. Fig. 10 shows the output characteristics of the PV panel.

As shown in this figure, the variation in sunshine causes changes in the voltages and currents produced by the panels; the MPPT system ensures the production of maximum power.

Let's start with the most important characteristic of any DC-DC converter in the event of variation, which is the DC bus voltage. The latter is represented in Fig. 11.

It is clearly evident by examining this result that, with the use of optimization by the ACO method, the adaptive regulator gives better performance, as we can clearly see that it minimizes the static

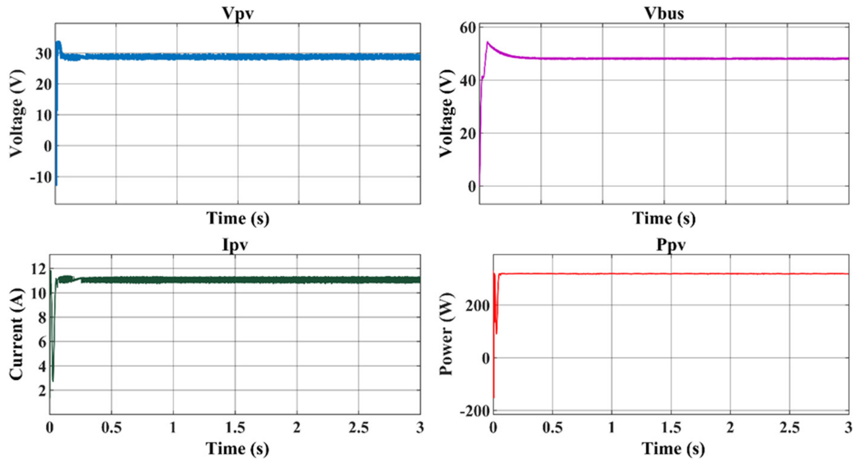

Fig. 5. PV output characteristics.

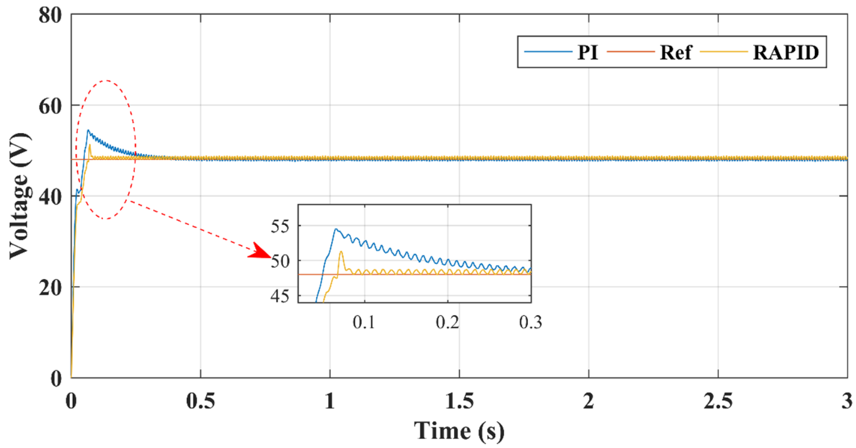

Fig. 6. Vdc battery side.

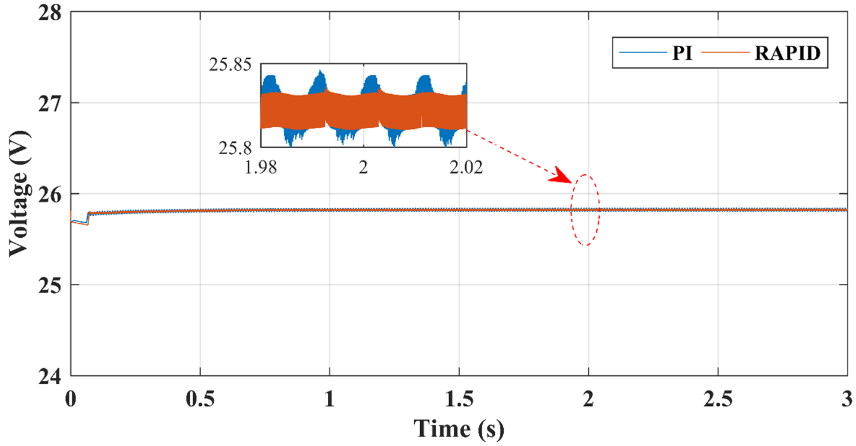

Fig. 7. Battery voltage.

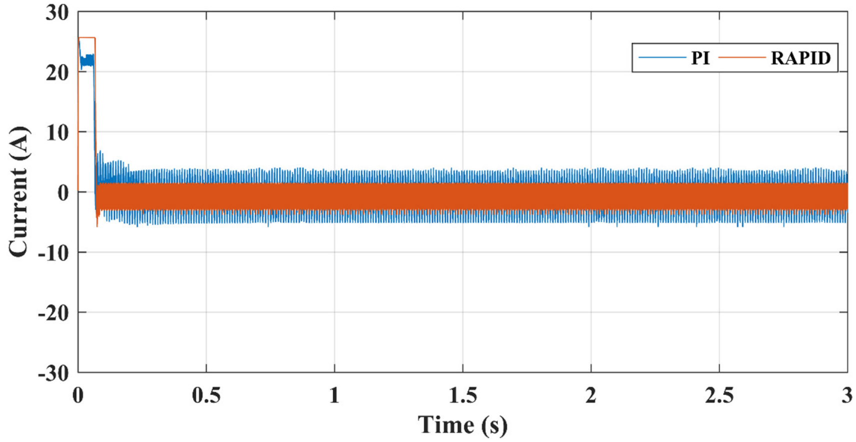

Fig. 8. Battery current.

error between the reference and the measurement. However, it should also be noted that in terms of response time, the RAPID alone responds very quickly compared to the RAPID based on the ACO.

This result can be validated by examining Fig. 12 and 13, which respectively represent the voltage and current of the battery. These figures reflect the behavior of the battery in the event of charging and discharging.

With a reduction in chattering, tuning the RAPID regulator using the ACO method improves the performance of this regulator.

Table VI gives a quantitative comparison of the results obtained in terms of response time, overrun, and static error.

TABLE III. SYSTEM RESPONSE CHARACTERISTICS

Properties	PI Classical	PI Adaptive RAPID
response time	0.087	0.085
Overshoot (%)	1.27%	0.581%
Steady State Error %	0.031	0.02

TABLE IV. OPTIMAL ACO CONTROLLER PARAMETERS VALUES

Parameters	Values
Number of ants	30
Number of iterations	100
A	0.8
B	0.2
Evaporation rate	0.7
Number of parameters	2
Lower bound	[0.01 0.05]
Upper bound	[10 10]
Number of nodes for each param	1000

Finally, Fig. 14 shows the obtained results of Vdc in the case of a classical PI regulator based on ACO and obtained results of the RAPID controller optimized by the ACO. As can be seen in this figure, the RAPID regulator based on ACO shows its performance in terms of final value compared to the classic regulator based on ACO. Note that the obtained gain in this case can be found in Table VII.

VIII. CONCLUSION

A new adaptive controller, which is the RAPID one based on a meta-heuristic optimization strategy using the ACO algorithm as an effective tested adaptive controller is proposed for the PV-battery system to ensure a good control of the battery. The buck-boost optimal regulation which is applied for charging/discharging the battery is controlled by the new controller with the objective of minimizing the input error of the controller.

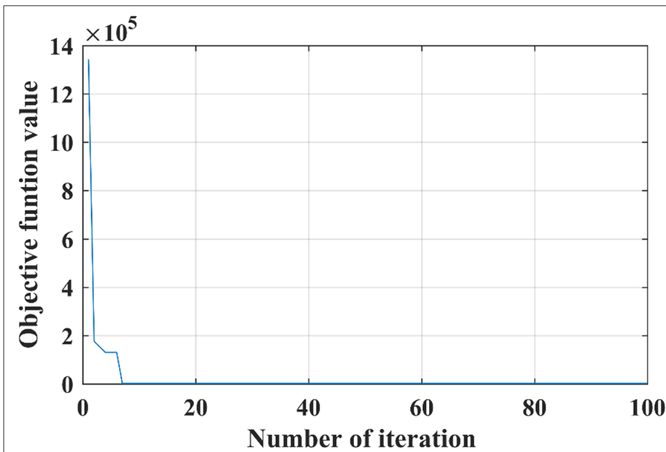

Fig. 9. Convergence curves for ACO algorithm.

TABLE V. PARAMETERS VALUE FOR KP AND KI IN THE CASE OF RAPID WITH AND WITHOUT ACO

	Kp	Ki
RAPID	0.5527	0.5527
ACO	0.7039	1.903

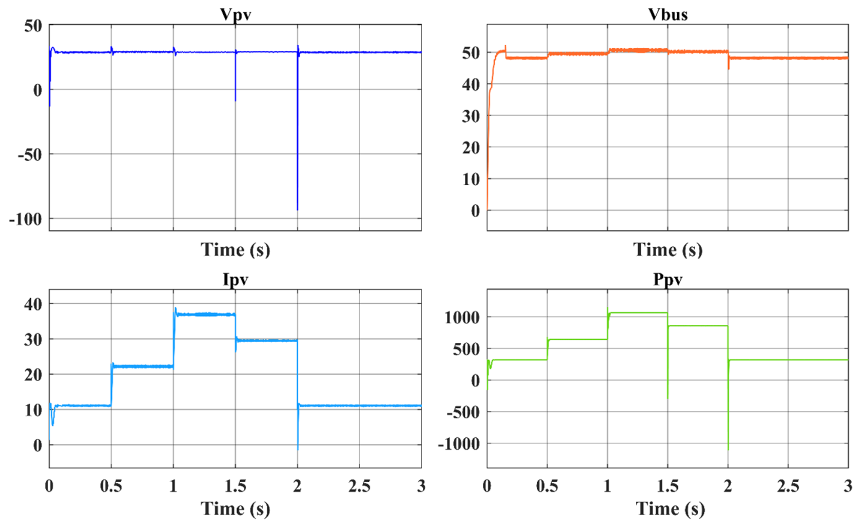

Fig. 10. Output characteristics of the PV panel (*G* variable).

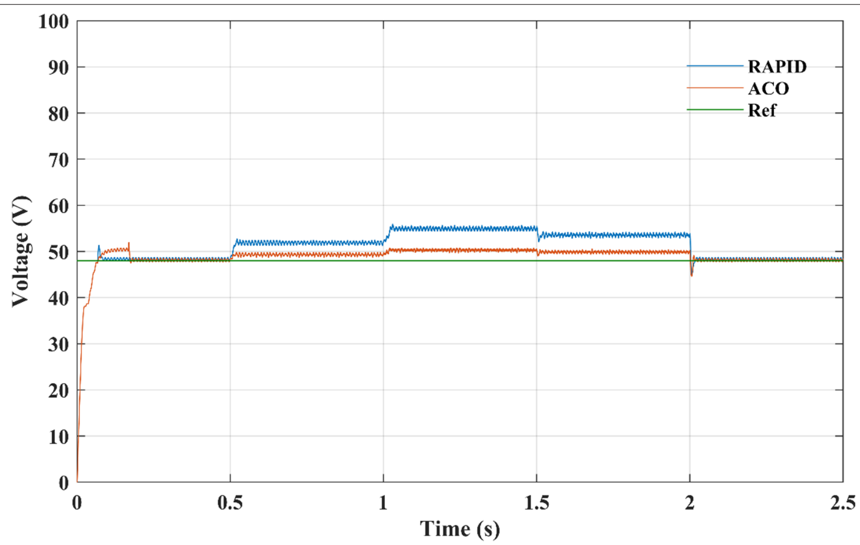

Fig. 11. Vdc battery side.

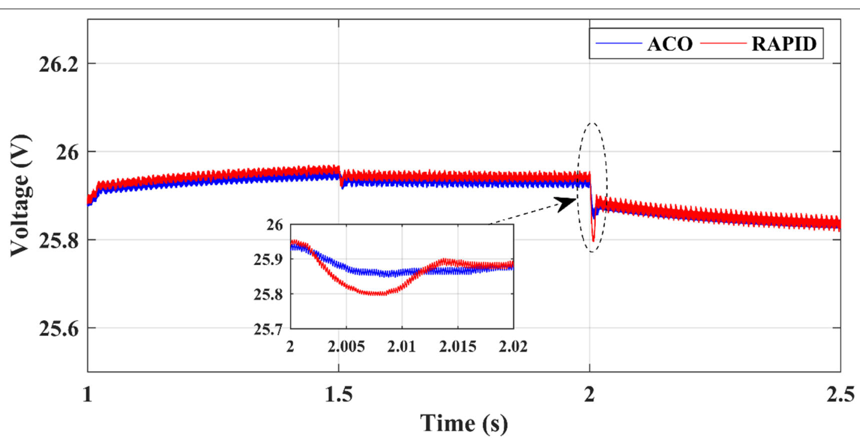

Fig. 12. Battery voltage.

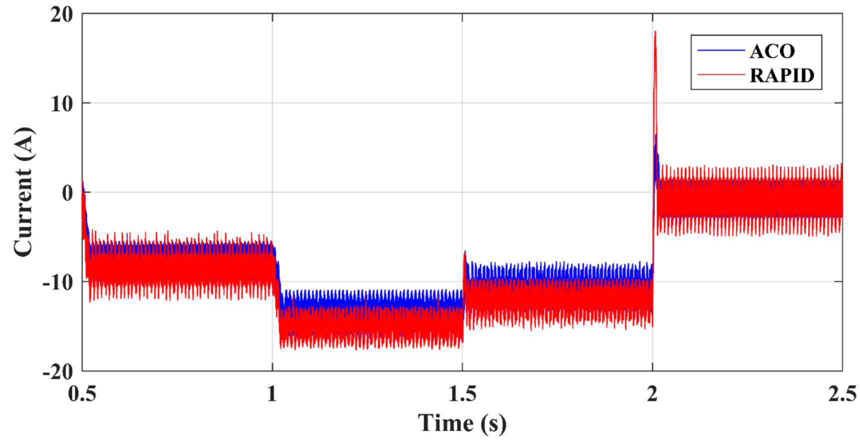

Fig. 13. Battery current.

This proposed combination was tested on a standalone PV system in two modes of working (permanent regime and variable regime), allowing us to better show the effect of the new ACO-RAPID controller.

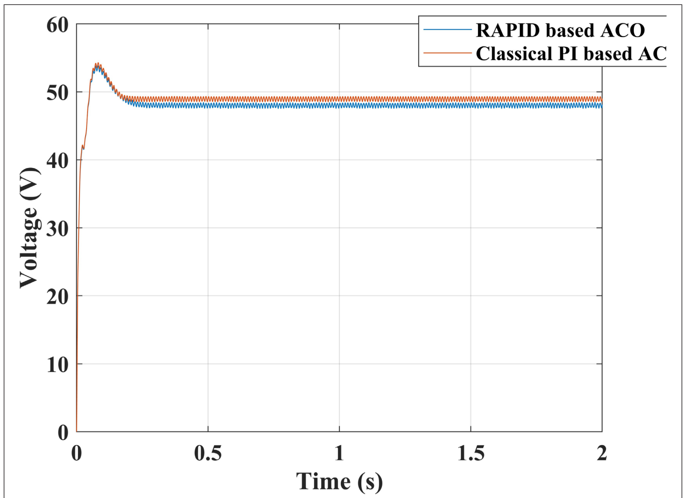

Fig. 14. Vdc voltage.

TABLE VI. COMPARATIVE RESULTS OF RESPONSE

Properties	RAPID based ACO		Only RAPID	
response time	0.083		0.085	
Overshoot (%)	0.58%		0.581%	
Steady State Error	[0 0.5]	[0.5 1]	[0 0.5]	[0.5 1]
	0.01	0.04	0.033	0.1

TABLE VII. PARAMETERS VALUE FOR KP AND KI IN CASE OF CLASSICAL PID AND RAPID BASED ACO

	Kp	Ki
RAPID based ACO	0.2293	0.77
Classical PID Based ACO	8.16	5.8467

The analysis of the obtained results shows that the RAPID controller is better than the classical PI controller-based trial & error technic, where the ACO method improves the RAPID efficiency for a PV-battery system control in terms of response time and overshoot. This confirms why the combination of why this combination between numerical methods and real devices is of practical value in controlling such type of system. As a perspective, this combination will be tested on a system connected to the network to observe the behavior of the battery in this context. Subsequently, this strategy can be tested on other systems that require good control, such as AC/DC converters, Multilevel Converters, etc.

Availability of Data and Materials: The data that support the findings of this study are available on request from the corresponding author.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – M.B.; Design – M.B., S.D.; Supervision – R.A.; Resources – M.B., S.B.; Materials – M.B.; Analysis and/or Interpretation – M.B., S.D.; Literature Search – M.B., S.D., S.B.; Writing – M.B., S.B., S.D.; Critical Review – R.A., A.T.

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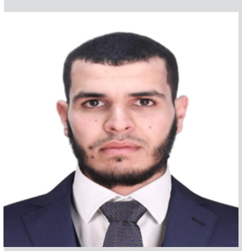

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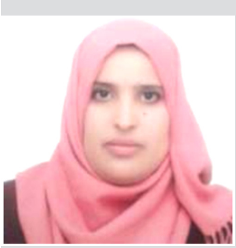

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