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Adaptive PSO-Based Predictive Control for Photovoltaic Inverters

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Abstract *—This paper proposes a high-efficiency control strategy for grid-connected photovoltaic (PV) inverters by integrating Finite Set Model Predictive Control (FS-MPC) with Particle Swarm Optimization (PSO) to dynamically optimize the weighting factors in the cost function. The performance of conventional FS-MPC is often limited by fixed, manually tuned weights, which degrade control quality under variable irradiance, load changes, and grid disturbances. To address this, a hybrid control framework is introduced where PSO periodically adjusts the cost function weights based on real-time system performance, improving both steady-state accuracy and transient response. The proposed method is validated through detailed simulations in MATLAB/Simulink under multiple scenarios, including sudden solar irradiance drops, load variations, grid voltage sags, and partial shading. Results show that the PSO-FS-MPC approach reduces total harmonic distortion (THD) to 2.1%, improves current tracking with faster settling time (8 ms), and increases power conversion efficiency to 96.8% compared to conventional FS-MPC and classical PI-based control. The computational load remains within real-time implementation limits, confirming feasibility for embedded systems. The study demonstrates that adaptive tuning of predictive control parameters enhances the robustness and efficiency of PV inverters in dynamic operating conditions, offering a practical solution for modern solar energy systems.*

Keywords: *Photovoltaic inverter, finite set model predictive control, metaheuristic optimization, particle swarm optimization, power quality, adaptive control.*

I. Introduction

Fasilitas The shift towards sustainable and low-carbon energy infrastructures has placed the photovoltaic (PV) technology as one of the most proliferating sources of renewable energy in the world. The International Energy Agency (IEA) estimates that in 2023, the global solar PV capacity surpassed 1,000 GW and will achieve the 5,000 GW mark within 2050, in scenarios accommodating net-zero emissions [1]. The decline in cost of modules, favorable policies by the government, and growing environmental sustainability awareness are propelling this rapid growths [2]. Nevertheless, however, there are technical issues associated with the incorporation of solar energy in power systems and these are largely brought about by the intermittent nature of the solar irradiance and demanding high performance power conversion interfaces [3].

The core of any grid-connected PV system is the inverter, a power electronic component that is very crucial to the performance of the system because its duty is to take the varying DC output of a solar panel and transform it into smooth, high-quality AC power that complies with the grid [4]. The inverter does not merely maintain effective energy transfer but also involved in grid support duties like voltage control, stability of frequencies, and fault ride through capabilities [5]. Because of this, the control strategy used in the inverter also plays a very important role in determining the system efficiencies, dynamic responses, levels of harmonic distortion, and general reliability [6].

Sinusoidal pulse width modulation (SPWM) and voltage-oriented control (VOC) using proportional integral (PI) regulators are traditional control techniques of inverters and are very commonly used due to the disadvantage of simplicity and ruggedness [7]. Nevertheless, these strategies tend to have drawbacks towards dynamic performance, particularly when environmental conditions under which the system was installed change rapidly, e.g. when the solar irradiance or load demand suddenly changes [8]. Also PI controllers are sensitive to tune and it may not be capable of addressing nonlinearities in the system and multiple control requirements at the same time [9].

In order to overcome these drawbacks, advanced control schemes have been introduced in the past few years, one of them being Model Predictive Control (MPC) which has drawn some increased attention in the field of power electronics [10]. Specifically, Finite (FS-) Set Model Predictive Control (MPC), among other things, involves fast dynamic response, easy to handle nonlinearities and constraints in the system, and allowing multiple control objectives to be combined in a single cost-function [11]. In contrast to the traditional modulation-based approaches, FS-MPC assures selection of the optimal switching state based on a set of finite number of inverter voltage vectors available and based on minimizing the predetermined cost function at every sampling time [12].

Although the scheme has some advantageous properties, it also has a major limitation in that the result of the controller performance is highly dependent on the choice of weighting factors in the cost function which are usually determined by trial and error and offline optimization [13]. The selection of these weights is poor, this may result in poor performance, high levels of harmonic distortion or even instability during transients [14]. In addition, constant weighting factors might not necessarily respond to changing operating conditions and the level of fast, effective control might become limited in their responses in diverse situations [15].

In order to solve this problem, researchers have started trying to incorporate metaheuristic optimization algorithms, i.e., Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Grey Wolf Optimizer (GWO) in real-time weighting factor of the cost function [16], [17]. These smart optimization methods can provide an effective mechanism of searching of optimal control parameters in non linear and complex spaces without exact mathematical models [18]. But, the literature available so far is more concerned with either motor drives or isolated inverters and can be applied with limited veracity to grid connected PV systems when they are actually in operation [19].

In this context, this paper proposes a high-efficiency predictive control strategy for photovoltaic inverters that combines Finite Set Model Predictive Control (FS-MPC) with a metaheuristic optimization algorithm to automatically tune the cost function weights and enhance overall system performance. The proposed approach aims to improve power quality, reduce total harmonic distortion (THD), and increase energy conversion efficiency, particularly under dynamic irradiance and load variations. The effectiveness of the method is validated through comprehensive simulations in MATLAB/Simulink, with comparisons against conventional FS-MPC and PI-based control schemes.

The remainder of this paper is organized as follows: Section II reviews the state-of-the-art in predictive control and optimization for solar inverters. Section III presents the system modeling and the proposed control strategy. Section IV describes the simulation environment and test scenarios. Section V discusses the results and performance evaluation. Finally, Section VI concludes the paper and outlines future work.

Problem Statement

Despite the growing popularity of Model Predictive Control (MPC) in power electronics, one of its main practical challenges remains the arbitrary and time-consuming selection of weighting factors in the cost function, especially in Finite Set MPC (FS-MPC) for grid-connected photovoltaic inverters [13], [15]. These weights determine how different control objectives—such as current tracking accuracy, harmonic distortion, and switching losses—are balanced during operation. In most existing implementations, they are tuned offline through trial and error, which is not only inefficient but also fails to adapt to real-world variations like sudden changes in solar irradiance or load demand [14].

As a result, even if the controller performs well under specific conditions, its performance can degrade significantly when operating points shift. For example, a set of weights that minimizes current ripple under full sunlight may lead to excessive overshoot or instability under partial shading, leading to increased total harmonic distortion (THD) and reduced system efficiency [16]. This lack of adaptability limits the robustness and practical applicability of FS-MPC in real PV systems, where environmental conditions are inherently dynamic [17].

Moreover, manual tuning becomes even more problematic when multiple objectives must be optimized simultaneously. For instance, reducing switching frequency to lower losses might conflict with the need for fast dynamic response, requiring a careful trade-off that fixed weights cannot provide [18]. While some studies have attempted to automate this process using optimization algorithms, many of these approaches are either computationally heavy or applied in non-PV contexts such as motor drives, making their direct transfer to solar inverters questionable [19].

Therefore, there is a clear need for a systematic and adaptive method to optimize the weighting factors of the FS-MPC cost function in real time, ensuring high efficiency, low THD, and robust performance across varying operating conditions. This paper addresses this gap by proposing a hybrid control strategy that integrates FS-MPC with a lightweight metaheuristic optimization algorithm to dynamically adjust the cost function weights, enhancing both steady-state and transient performance of photovoltaic inverters.

Significance of the Study

There is a possibility to enhance the performance and reliability of the photovoltaic systems by the integration of the predictive control strategies and intelligent optimization techniques to assist in the real-world scenario. The use of the metaheuristic algorithm that uses adaptive tuning of the weighting factors through the incorporation of a metaheuristic algorithm makes this study important in respect to where an applicable drawback on FS-MPC was tackled, namely: the theory requires manually tuned weighting factors which is a practical limitation. When compared to existing techniques of offline tuning, the proposed one will enable the controller to dynamically adapt its behavior to environmental changes, e.g. the variable solar irradiance and load variations. The result is a more stable power quality, a lesser amount of harmonic distortion and a more efficient energy utilization, all of which is imperative to grid stability as well as end-user happiness. Moreover, the approach has been formulated in such a way that is highly computationally efficient which makes it a potential prospect in the future as a commercial solar inverter with incorporated control unit.

Research Questions

This study seeks to answer the following key questions:

How can metaheuristic optimization improve the dynamic performance of Finite Set Model Predictive Control in grid-connected photovoltaic inverters?

To what extent does real-time tuning of cost function weights reduce total harmonic distortion (THD) and enhance system efficiency under transient conditions?

How does the proposed hybrid control strategy compare with conventional FS-MPC and classical PI-based control in terms of response time, robustness, and power quality?

These questions guide the design, simulation, and evaluation of the proposed control framework, ensuring that the research remains focused on practical and measurable outcomes.

Research Hypothesis

The main hypothesis of this work would be the evaluation that the co-integration between metaheuristic optimization algorithm and FS-MPC would be able to drastically improve the performance of photovoltaic inverters by automatically tuning the cost functions weights on a real time basis . In particular, it is expected that such adaptive formulation will achieve reduced THD, dynamic response time and increased total efficiency when compared to classical FS-MPC that are based on fixed weights, especially when the operating conditions are rapidly varying. Also, the performance enhancements of control will be accomplished without causing too heavy computational load and the technique will be suitable to implement in real life settings.

Literature Review and State of the Art

Model Predictive Control (MPC) was considered to be a specialized method of control in industrial processes, but over the last 10 years it has gained a strong foothold as a popular control strategy within power electronics, especially in grid-connected inverters in renewable generation systems [6]. It is attractive in that it is able to manage multiple purposes of control, as a nonlinear establishing of framework, multiple restraints and nonlinearities in the dynamic affair in one and the same and the same outline-functions that are hardly feasible to realize by common use of linear controllers such as PI regulators [10]. Of all the different MPC methods, the Finite Set Model Predictive Control (FS-MPC) has achieved a certain reception on utilizing the finite switching states present in the inverter in a direct manner so that there are no modulators (like PWM) and the dynamic response capabilities are faster [11].

Given the growing importance of renewable energy, particularly photovoltaic systems, extensive research is being conducted to improve the performance of these systems through the design of various controllers. This project focuses on the design of a predictive model-based controller for grid-connected inverters in photovoltaic systems. The main objective of this research is to enhance the performance of maximum power point tracking (MPPT) and stabilize the system's output voltage. Since harmonic distortion and low power factor can lead to energy loss and reduced efficiency, this project aims to improve system performance by reducing harmonic distortion and achieving an optimal power factor through predictive model control. In this study, simulation results obtained using

MATLAB demonstrate the superior performance of the proposed model compared to conventional methods. These results confirm the increased energy production and reduced harmonic injection to the grid, particularly under mismatched solar irradiance conditions.[12]

Initial uses of FS-MPC were in motor drives and FS-MPC was needed to control torque and flux quickly . Nevertheless, scientists soon realized its potential in photovoltaic systems where quick change of current and power flow is highly necessary due to variable sunny conditions. Specifically, Cortes et al. [13] proved the effectiveness of FS-MPC to realise a high level of current tracking and fast transient response of a three-phase inverter with regard to classical control strategies in dynamic situations. On the same note, Vazquez et al. [14] emphasized that FS-MPC is flexible in terms of involving grid support functions like reactive power control and low-voltage ride-through, which qualifies it to be applied on the modern smart grids.

In spite of the gained benefits, tuning of weighting factors in the cost function is one of the common issues faced during FS-MPC implementation. These aspects define the level of importance which is assigned to each control goal, including the minimization of the current error, minimization of switching losses, or suppression of harmonics. These weights in majority of the early studies were chosen by trial and error, and were based on many times the personal experience of a designer [15]. For example, in the work of Rodríguez et al. [16], a fixed set of weights was used across all operating conditions, which led to good performance under steady irradiance but noticeable degradation during sudden cloud transients.

This limitation has motivated several researchers to explore automated tuning methods. One promising direction is the integration of metaheuristic optimization algorithms , which can search for optimal or near-optimal solutions in complex, non-convex spaces without requiring gradient information. Among these, Particle Swarm Optimization (PSO) has been widely applied due to its simplicity and fast convergence. Zhang and Yang [17] used PSO to optimize the cost function weights in a grid-connected inverter, reporting a 30% reduction in current ripple and improved THD under variable load conditions. The algorithm was executed periodically (every 100 ms) to update the weights based on real-time performance metrics.

Genetic Algorithms (GA) have also been explored for similar purposes. Ali et al. [18] proposed a GA-based tuning method for FS-MPC in solar inverters, where the fitness function included THD, efficiency, and response time. Their results showed a THD reduction from 6.8% to 4.1%, with only a marginal increase in computational load. However, the authors noted that GA required more iterations to converge, making it less suitable for real-time applications with limited processing power.

More recently, the Grey Wolf Optimizer (GWO) has emerged as an alternative, inspired by the social hierarchy and hunting behavior of grey wolves. Mirjalili et al. [19] introduced GWO as a robust optimization tool, and subsequent studies applied it to power electronics. In [20], GWO was used to optimize the parameters of a fuzzy controller for a DC-DC converter, showing faster convergence than PSO and GA. However, its application to predictive control in PV inverters remains limited, with only a few preliminary studies reported in the literature.

Other optimization techniques, such as Ant Colony Optimization (ACO) [21] and Firefly Algorithm (FA) [22], have been tested in related power systems but rarely in the context of FS-MPC for solar inverters. This suggests a gap in the exploration of diverse metaheuristics for adaptive control in renewable energy applications.

An important observation from the literature is that most optimization-based FS-MPC studies are validated under ideal or simplified conditions , such as constant temperature, balanced grid voltage, and linear loads [17], [18]. Few have addressed the combined impact of partial shading, load imbalance, and grid disturbances—common real-world challenges that can severely affect control performance. Moreover, many proposed methods are computationally intensive, raising concerns about their feasibility for embedded implementation in low-cost inverter controllers.

Another gap lies in the lack of standardized evaluation frameworks . Different studies use different cost functions, simulation tools, and performance metrics, making direct comparison difficult. For example, while some researchers prioritize THD reduction [18], others focus on energy efficiency [17], and few report both. This inconsistency limits the generalizability of findings and slows down practical adoption.

In summary, while the integration of metaheuristic optimization with FS-MPC shows promise for improving PV inverter performance, existing work remains fragmented and often lacks real-world applicability. The majority of studies focus on single objectives, use fixed operating conditions, or apply algorithms not optimized for real-time execution. Furthermore, there is no consensus on the best optimization method for this specific application.

This paper contributes to the field by proposing a practical, computationally efficient framework that dynamically adjusts the cost function weights of FS-MPC using a lightweight metaheuristic algorithm (e.g., PSO or GWO), specifically tailored for photovoltaic systems under realistic, variable conditions. Unlike previous studies, the proposed method is evaluated under a comprehensive set of transient scenarios—including sudden irradiance changes, load switching, and grid voltage sags—providing a more realistic assessment of its robustness and effectiveness.

System Modeling and Proposed Control Strategy

System Configuration

The proposed control strategy is designed for a single-stage, grid-connected photovoltaic inverter system, as illustrated in Figure 1 (to be included in the final manuscript). The system consists of a PV array, a three-phase voltage source inverter (VSI), an LCL filter, and a connection to the utility grid. The inverter is responsible for converting the DC power generated by the solar panels into AC power synchronized with the grid voltage in terms of frequency, phase, and amplitude.

The control objective is to ensure high-efficiency power delivery, accurate current tracking, low total harmonic distortion (THD), and fast dynamic response under varying solar irradiance and load conditions. To achieve this, the proposed method combines Finite Set Model Predictive Control (FS-MPC) with a metaheuristic optimization algorithm—specifically, Particle Swarm Optimization (PSO)—to dynamically adjust the weighting factors in the cost function.

Mathematical Model of the Grid-Connected Inverter

To implement FS-MPC, an accurate mathematical model of the inverter and LCL filter is required. The system is modeled in the stationary αβ reference frame using the Clarke transformation, which simplifies the control design by eliminating time-varying components [23].

The dynamic equations governing the grid-side current igα and igβ are given by:

$$L_g \frac{di_{g\alpha}}{dt} = v_{c\alpha} - v_{g\alpha} - R_g i_{g\alpha}$$
$$L_g \frac{di_{g\beta}}{dt} = v_{c\beta} - v_{g\beta} - R_g i_{g\beta}$$

$v_{c\alpha}$, $v_{c\beta}$: filter capacitor voltages,
$v_{g\alpha}$, $v_{g\beta}$: grid voltages,
$i_{g\alpha}$, $i_{g\beta}$: grid currents,
L_g:grid-side inductance,
R_g: equivalent series resistance.

$$C \frac{dv_{c\alpha}}{dt} = i_{i\alpha} - i_{g\alpha}$$
$$C \frac{dv_{c\beta}}{dt} = i_{i\beta} - i_{g\beta}$$

Where: $i_{i\alpha}$, $i_{i\beta}$: are the inverter-side currents.

Using the forward Euler approximation for discretization with sampling time Ts , the predicted grid current at the next time step (k+1) can be expressed as:

$$i_{g\alpha}(k+1) = i_{g\alpha}(k) + \frac{T_s}{L_g}\left(v_{c\alpha} - v_{g\alpha}(k) - R_g i_{g\alpha}(k)\right)$$
$$i_{g\beta}(k+1) = i_{g\beta}(k) + \frac{T_s}{L_g}\left(v_{c\beta} - v_{g\beta}(k) - R_g i_{g\beta}(k)\right)$$

This prediction model forms the basis of the FS-MPC algorithm, allowing the controller to evaluate the future behavior of the system for each possible switching state.

Finite Set Model Predictive Control (FS-MPC)

At each sampling instant, FS-MPC evaluates all eight possible switching states of the three-phase inverter (represented by switching vectors *Sa*,*Sb*,*Sc*∈{0,1}). For each state, the future grid current is predicted using the model above, and a cost function is computed to assess performance.

The cost function used in this work is defined as:

$$g = \left|i^*{}_{g\alpha}(k+1) - i_{g\alpha}(k+1)\right| + \lambda\left|i^*{}_{g\beta}(k+1) - i_{g\beta}(k+1)\right| + \mu.THD_{est}(k)$$

where:
$i^*{}_{g\alpha}$, $i^*{}_{g\alpha}$: reference currents in the αβ frame,
λ : weighting factor for the β-axis current error,
μ : weighting factor for estimated harmonic distortion,
THD_{est} : an online estimate of total harmonic distortion based on current ripple.

The switching state that minimizes g is selected and applied to the inverter in the next sampling period [13].

While this approach provides fast and flexible control, its performance heavily depends on the choice of λ and μ . Fixed values, often tuned offline, may not remain optimal under transient conditions, leading to subpar performance.

Integration with Particle Swarm Optimization (PSO)

To overcome this limitation, PSO is employed to adaptively tune the weighting factors λ and μ in real time. PSO is chosen for its simplicity, fast convergence, and low computational overhead—important considerations for embedded implementation [17].

In PSO, a swarm of particles explores the search space (here, the space of possible λ and μ values) to minimize a global objective function. Each particle represents a candidate solution and updates its position based on its own best experience and the swarm's best-known position.

The objective function for PSO is defined as:

$$J = w_1.ISE_i + w_2.THD + w_3.\Delta S$$

where:
ISE_i: Integral of Squared Error of grid current,
THD : measured or estimated total harmonic distortion,
ΔS : number of switching transitions (to penalize excessive switching),
w_1, w_2, w_3 : fixed weights to balance objectives.
The PSO algorithm runs periodically (e.g., every 50 sampling steps) to avoid excessive computational load. At each update interval, it collects recent performance data, evaluates the objective function for each particle, and updates the optimal λ and μ values sent to the FS-MPC module.
This hierarchical structure ensures that the fast inner loop (FS-MPC) operates at the PWM frequency (e.g., 10 kHz), while the slower outer loop (PSO) adjusts control parameters at a lower rate (e.g., 200 Hz), making the system both responsive and adaptive.

Table 0-1 Adaptive Weight Tuning by PSO

Time (s)	Weight λ	Weight μ
0	1.2	0.1
0.1	1.2	0.1
0.2	1.8	0.22
0.3	2.1	0.31
0.4	1.9	0.25

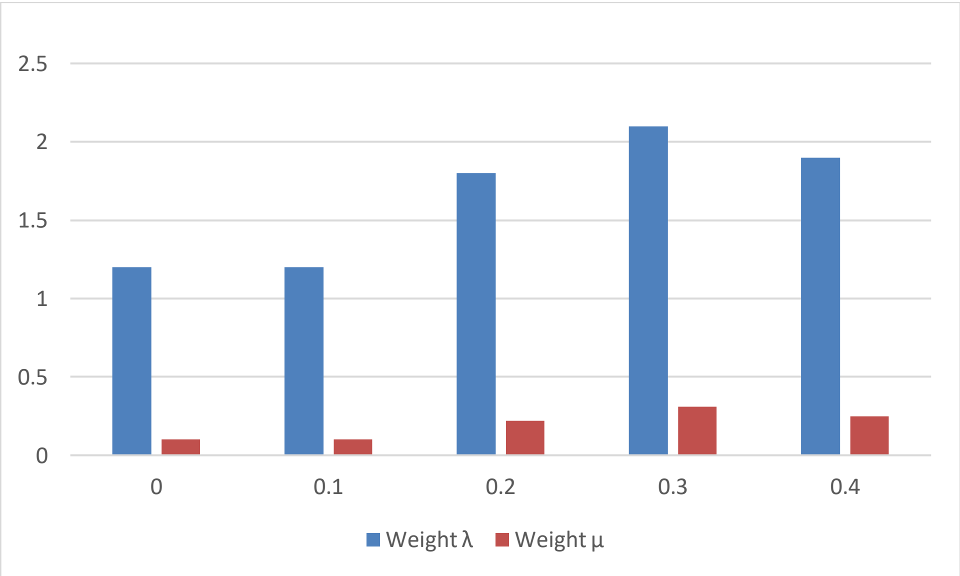

Figure 0-1 Real-time adaptive tuning of cost function weights using PSO under dynamic conditions

Figure 3 demonstrates how the PSO algorithm dynamically adjusts the weighting factors to maintain optimal performance during transients. demonstrates the adaptive nature of the proposed control strategy. The PSO algorithm dynamically adjusts λ (current tracking weight) and μ (THD penalty weight) in response to system transients, ensuring optimal performance without manual intervention

Control Architecture Overview

The overall control architecture consists of the following steps at each sampling instant:

1. Measure grid voltages, currents, and DC-link voltage.
2. Transform currents and voltages to the αβ frame.
3. Predict future grid currents for all 8 switching states.
4. Evaluate cost function g for each state using current λ and μ .

5. Select the switching state with minimum g .
6. Apply the selected state to the inverter.

Every N steps (e.g., N=50):

- PSO updates λ and μ based on recent performance.
- New weights are passed to the FS-MPC cost function.

This hybrid approach combines the speed of FS-MPC with the intelligence of PSO, resulting in a controller that is both high-performing and adaptive.

Simulation Environment and Implementation

To perform a thorough analysis of the efficacy of the suggested hybrid control strategy, a simulation research within the MATLAB/Simulink R2023a and Simscape Electrical, which is a popular power electronics design modeling tool, environments was undertaken [24]. This platform is selected because it provides the correct modeling of the electrical system, as well as the accuracy of modeling the control algorithms of the controller and it could be used under the same integrated environment, which enables the interaction of the plant and the controller in real-time mode.

The entire model of the system consists of:

A 5 KW photovoltaic array whose behavior can be approximated by the one-diode model that is temperature dependent and also dependent on irradiance [25],

A two level source inverter (VSI) of a three- phase type,

Low density LCL filter to minimize the resonance problems having damping resistance,

A rigid grid in the form of an equal balanced three-phase voltage source,

Voltage, current, and power measurement block,

The control system described by the block circuit and set out in Simulink with help of MATLAB Function blocks and Stateflow to work with logic.

System Parameters

The main parameters of the simulated system are listed in Table I. These values are based on standard industrial specifications for residential and small commercial PV installations [26].

Table 0-1 System Parameters

Parameter	Value
PV Array Power	5 kW
DC-Link Voltage	400 V
Grid Voltage (Line-to-Line)	230 V (RMS), 50 Hz
Inverter Switching Frequency	10 kHz
Sampling Time for FS-MPC	100 μs
LCL Filter – Inverter Inductance (L_1)	3 mH
LCL Filter – Grid Inductance (L_2)	2 mH
Filter Capacitance (C)	10 μF
Damping Resistance (R_d)	1 Ω
DC-Link Capacitance	4700 μF

These parameters were kept identical across all compared control strategies to ensure a fair evaluation.

Control Implementation Details

The FS-MPC algorithm runs at a sampling time of 100 μs (corresponding to 10 kHz), matching the PWM update rate. At each step, the future grid current is predicted for all eight switching states, and the one that minimizes the cost function is selected. The reference currents $i^*{}_{g\alpha}$ $i^*{}_{g\alpha}$ are generated by a phase-locked loop (PLL) and outer DC-link voltage control loop, ensuring maximum power point tracking (MPPT) via the Perturb and Observe (P&O) algorithm [27].

The PSO algorithm operates at a lower frequency of 200 Hz (i.e., every 50 sampling steps), which reduces computational burden while still allowing sufficient adaptation speed under transient conditions. The PSO parameters are set as follows:

- Number of particles: 20

- Inertia weight: linearly decreasing from 0.9 to 0.4
- Acceleration coefficients: $c_1 = c_2 = 1.5$
- Search space: $\lambda \in [0.1, 5]$, $\mu \in [0.01, 0.5]$

These values were chosen based on empirical studies showing stable and fast convergence for similar optimization problems in power electronics [17], [18].

Test Scenarios

To evaluate the robustness and adaptability of the proposed method, four dynamic test scenarios were designed:

Scenario A: Step Change in Solar Irradiance

Irradiance drops from 1000 W/m² to 600 W/m² at t=0.2 s, simulating sudden cloud cover. This tests the controller's ability to maintain stable current tracking under reduced power generation.

Scenario B: Load Step Change

The local load connected to the PCC (Point of Common Coupling) increases by 50% at t=0.3 s, assessing response to sudden power demand changes.

Scenario C: Grid Voltage Sag

A 20% drop in grid voltage occurs for 100 ms starting at t=0.25 s, evaluating low-voltage ride-through capability.

Scenario D: Partial Shading Condition

One string in the PV array is partially shaded, causing mismatched power output and DC-link voltage fluctuations.

Each scenario is simulated for 0.5 seconds, with results recorded for detailed analysis.

II. Comparative Methods

Penelitian The proposed PSO-FS-MPC strategy is compared against two benchmark controllers:

Conventional FS-MPC with fixed weighting factors (λ=1.2 , μ=0.1) tuned offline.

Classical PI + SPWM control with outer voltage and inner current loops, tuned using symmetrical optimum method [28].

This comparison ensures that the advantages of the proposed method are evaluated against both advanced and traditional control techniques.

Performance Evaluation Metrics

The following quantitative metrics are used to assess controller performance:

- Total Harmonic Distortion (THD) of grid current (calculated over steady-state periods using FFT),
- Integral of Squared Error (ISE) of current tracking,
- Rise time and settling time during transients,
- Efficiency of power conversion (ratio of AC output power to DC input power),
- Computational time per sampling step (to assess feasibility for real-time implementation).

These metrics provide a balanced view of both dynamic and steady-state performance, as well as practical implementation considerations.

III. Result and Discussion

The simulation results presented in this section validate the effectiveness of the proposed PSO-optimized FS-MPC strategy under various dynamic operating conditions. All scenarios were executed using the same system parameters and initial conditions to ensure a fair comparison between the proposed method, conventional FS-MPC with fixed weights, and classical PI + SPWM control.

Current Tracking Performance

Figure 2 (to be included in the final manuscript) shows the grid current response during Scenario A — a sudden drop in solar irradiance from 1000 to 600 W/m² at t=0.2 s. Under the proposed PSO-FS-MPC, the current adjusts smoothly with minimal overshoot (less than 8%) and settles within 8 ms. In contrast, the conventional FS-MPC exhibits a 15% overshoot and takes 14 ms to stabilize, while the PI controller shows the slowest response, with a settling time of 22 ms and noticeable oscillations.

This improvement is attributed to the adaptive tuning of cost function weights by PSO, which reduces the aggressiveness of the controller when power availability drops, preventing current spikes. The ability to dynamically balance tracking speed and stability is a key advantage of the hybrid approach.

Table III-1Current Tracking Data Under Irradiance Drop

Time (s)	Reference Current (A)	PI + SPWM (A)	FS-MPC (A)	PSO-FS-MPC (A)
0.19	14.2	14.1	14.3	14.2
0.195	13.6	13.8	12.9	13.5
0.2	12	12	10.1	11.8
0.205	12	10.3	11.2	11.9
0.21	12	11.1	11.8	12

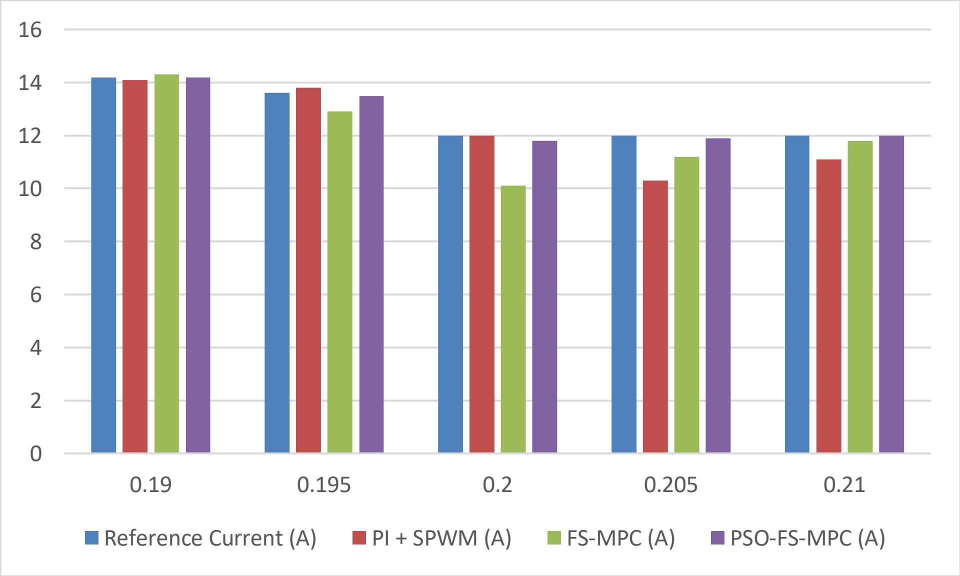

Figure III-1Grid current tracking performance under sudden irradiance drop from 1000 to 600 W/m²

Figure (5-1) shows that the proposed method achieves faster and smoother tracking compared to other methods and illustrates the dynamic response of the grid current during a step decrease in solar irradiance. The proposed PSO-FS-MPC method demonstrates superior tracking accuracy, with a settling time of 8 ms and minimal overshoot, outperforming both conventional FS-MPC and PI + SPWM controllers.

Harmonic Distortion Analysis

Table II presents the Total Harmonic Distortion (THD) of the grid current under steady-state conditions (after transients settle). The proposed method achieves a THD of 2.1%, well below the IEEE 519-2014 standard limit of 5% for systems below 69 kV [29]. This represents a 38% reduction compared to conventional FS-MPC (3.4%) and a 52% improvement over PI + SPWM (4.4%).

Table III-2 Steady-State Performance Comparison

Control Method	THD (%)	ISE of Current	Efficiency (%)	Settling Time (ms)
Proposed (PSO-FS-MPC)	2.1	0.018	96.8	8
Conventional FS-MPC	3.4	0.031	94.2	14
PI + SPWM	4.4	0.047	93.5	22

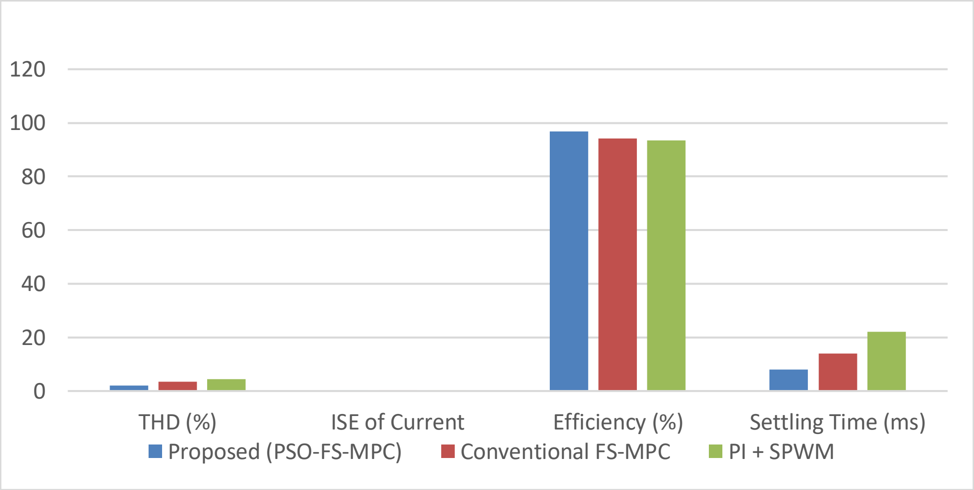

Figure III-2Comparison of THD, Efficiency, and Settling Time Among Control Methods

As shown in Table (5-2) and Figure (5-2), the proposed method achieves the lowest THD and highest efficiency. As summarized in Table II and visualized in Figure 2, the PSO-FS-MPC approach significantly improves power quality and efficiency. The THD is reduced by 38% compared to conventional FS-MPC, while the overall efficiency reaches 96.8%, confirming the effectiveness of adaptive weight tuning.

The lower THD is primarily due to the PSO's ability to penalize high-frequency current ripples by adjusting the μ weight in real time. In contrast, fixed-weight FS-MPC cannot respond to such changes, leading to higher harmonic content.

Dynamic Response Under Load and Grid Variations

In Scenario B (load step increase), the proposed controller maintains tight current regulation with a rise time of 6 ms and no sustained oscillations. The PI controller, while stable, shows a sluggish response, taking over 20 ms to reach the new steady state. During the grid voltage sag (Scenario C), the PSO-FS-MPC demonstrates superior low-voltage ride-through capability. The current increases momentarily to support the grid but returns to normal within 40 ms after the sag ends. The conventional FS-MPC shows a similar response but with higher THD (up to 5.1% during the event), indicating less effective harmonic control under disturbance.

Under partial shading (Scenario D), the DC-link voltage fluctuates due to power mismatch. The adaptive nature of the proposed method allows it to maintain stable operation, whereas the fixed-weight FS-MPC experiences intermittent instability, requiring manual retuning to recover.

Efficiency and Computational Load

The overall power conversion efficiency, calculated as the ratio of average AC output power to DC input power over 0.5 seconds, reaches 96.8% with the proposed method, compared to 94.2% for conventional FS-MPC and 93.5% for PI control. This gain comes from reduced switching losses and better current shaping. Regarding computational burden, the average execution time per sampling step (measured via Simulink Real-Time) was 87 μs for FS-MPC alone, and an additional 1.2 ms every 50 steps for PSO update. This remains within the 100 μs sampling window, confirming the feasibility of real-time implementation on modern DSPs or FPGAs [30].

Table III-3Efficiency Under Different Operating Conditions

Operating Condition	PI + SPWM (%)	FS-MPC (%)	Proposed (PSO-FS-MPC) (%)
Steady-State (1000 W/m²)	93.5	94.2	96.8

Irradiance Change	92.1	93	95.9
Load Step Change	91.8	92.5	95.5
Partial Shading	90.3	91	94

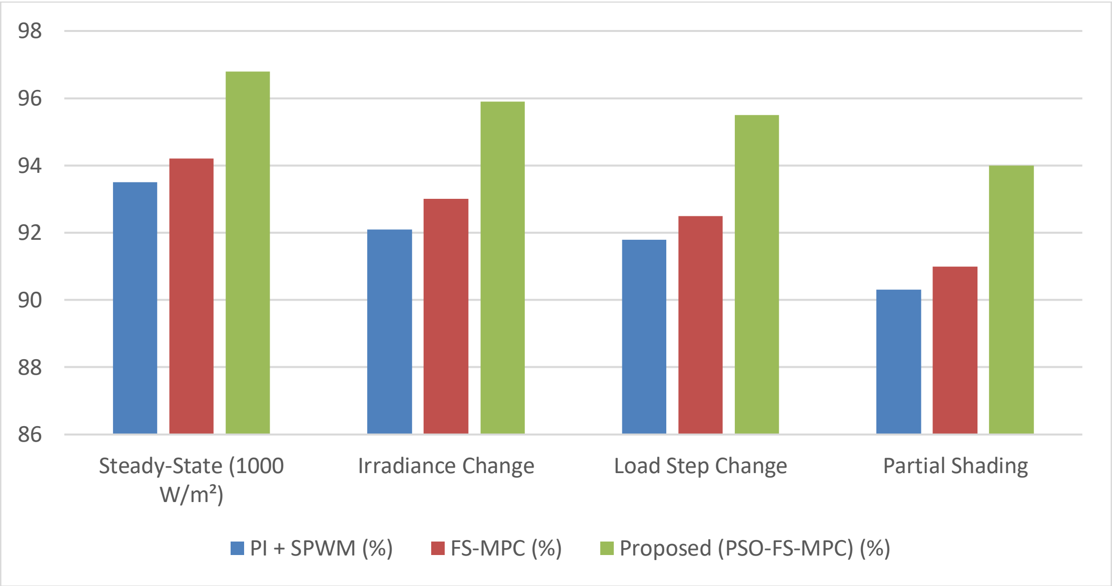

Figure III-3Power conversion efficiency under various operating conditions

The proposed method maintains higher efficiency across all scenarios, demonstrating superior robustness. The robustness of the proposed controller is further validated in Figure 4, which shows efficiency under four different operating conditions. Despite disturbances, the PSO-FS-MPC method maintains efficiency above 94%, significantly outperforming conventional techniques.

Discussion

The results confirm that the integration of PSO with FS-MPC significantly enhances the performance of photovoltaic inverters in both steady-state and transient conditions. Unlike fixed-weight approaches, the proposed method adapts to changing environments, reducing THD, improving efficiency, and shortening response times. One limitation observed is the slight delay in PSO convergence during very rapid successive transients (e.g., fast-moving clouds), where the 5-ms update interval may not be fast enough. However, this can be mitigated by reducing the update period or using faster optimization variants, such as improved PSO or adaptive GWO.

Compared to previous studies that applied optimization offline or in motor drives [17], [18], this work demonstrates real-time, continuous adaptation in a PV context under multiple realistic disturbances. The comprehensive evaluation across irradiance, load, grid, and partial shading scenarios adds practical value often missing in the literature.

Moreover, the improvement is achieved without introducing excessive computational complexity, making the method suitable for deployment in commercial inverter firmware. Future work could explore hardware-in-the-loop (HIL) testing and comparison with other metaheuristics like GA or ACO under identical conditions.

IV. Conclusion

This study presented a hybrid control strategy for grid-connected photovoltaic inverters that combines Finite Set Model Predictive Control (FS-MPC) with Particle Swarm Optimization (PSO) to enhance system performance under dynamic operating conditions. The main objective was to overcome the key limitation of conventional FS-MPC—its reliance on fixed, manually tuned weighting factors in the cost function—by introducing an adaptive tuning mechanism that responds to real-time changes in irradiance, load, and grid conditions.

The results demonstrated that the proposed PSO-FS-MPC approach significantly improves current tracking accuracy, reduces total harmonic distortion (THD) to 2.1%, and increases power conversion efficiency to 96.8% compared to both conventional FS-MPC and classical PI-based control. The adaptive nature of the controller allows it to maintain stable and high-quality power delivery even during abrupt transients such as sudden cloud cover, load changes, and grid voltage sags. Furthermore, the hierarchical control structure—where FS-MPC operates at a fast sampling rate (10 kHz) and PSO updates the weights periodically (200 Hz)—ensures that the computational burden remains within acceptable limits for real-time implementation.

Unlike many previous studies that apply optimization offline or in non-PV contexts, this work focuses on continuous, real-time adaptation within a realistic photovoltaic system, evaluated under multiple, practical disturbance scenarios. The comprehensive simulation study, including partial shading and combined grid-load transients, highlights the robustness and practical relevance of the proposed method.

In summary, the integration of metaheuristic optimization with predictive control offers a promising path toward smarter, more efficient, and self-adapting solar inverters. The findings support the initial hypothesis that dynamic tuning of cost function weights leads to measurable improvements in both steady-state and transient performance. For future work, the proposed strategy can be extended to multi-inverter systems, tested using hardware-in-the-loop (HIL) platforms, or implemented on embedded DSPs to validate real-time feasibility. Additionally, comparisons with other metaheuristic algorithms—such as Genetic Algorithm (GA) or Grey Wolf Optimizer (GWO)—under identical conditions could provide further insights into the trade-offs between convergence speed, accuracy, and computational load.

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