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Optimizing Volt-Var Control in PV-Integrated Microgrids Using Harmony Search Algorithm for Power Distribution Systems

Andrei Popescu^{1*}, Mihai Ionescu¹, Elena Stan²

Abstract

This study introduces a coordinated control approach to address the challenge of volt-var optimization (VVO), incorporating load tap-changing transformers, step-voltage regulators, and switched-capacitor banks, along with a photovoltaic (PV)-integrated microgrid. The harmony search (HS) metaheuristic algorithm was applied to efficiently compute the globally optimal operating parameters for these devices, ensuring robust performance across fluctuating operating conditions. The key aims of the volt-var control strategy were to achieve substantial reductions in active power losses, peak demand, and voltage deviations throughout the distribution system, while simultaneously maintaining bus voltages within acceptable regulatory limits under all possible load scenarios. The optimization problem is a mixed-integer nonlinear program with discrete decision variables, binary variables representing capacitor bank switching states (on/off), integer variables for voltage regulator tap positions, continuous variables for the microgrid's injected current, and nonlinear network power-flow constraints. The proposed methodology was tested and validated on the standard IEEE 13-node distribution test feeder. Time-series simulations used realistic daily load profiles from the main grid, along with the microgrid's PV output, both resolved at 15-minute intervals. All power flow computations were carried out with OpenDSS (version 9.5.1.1, released in 2022), an established open-source distribution system analysis tool. The developed control framework supports both real-time operation and long-term planning studies. Simulation results showed that the integrated volt-var coordination significantly reduced total active power losses, lowered peak demand, and effectively mitigated voltage variations across the network.

Keywords Microgrid, Optimization, Distribution systems, DERs, Power loss, Power management

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Introduction

A sophisticated strategy for managing electrical grids, known as volt-var control and optimization (VVC/VVO), is implemented in power distribution networks to enhance reactive power (VAR) flow and maintain appropriate voltage profiles. This approach boosts system reliability, reduces energy dissipation, and increases overall electricity efficiency. The VVC component focuses on real-time adjustment of voltage and reactive power, relying on equipment such as capacitor banks, voltage regulators, and on-load tap changers (OLTCs). Meanwhile, the VVO aspect focuses on reducing energy losses, achieving peak efficiency, and ensuring voltages comply with standards, all while lowering power waste and operational expenses. Given the combination of binary, integer, and continuous variables—alongside discrete and

real-valued parameters—this constitutes one of the most challenging optimization tasks, characterized by its nonconvexity and nonlinearity.

Roughly 10% of the electricity produced at generation facilities is lost during the transmission and distribution process to end users. Distribution networks account for approximately 40% of these total losses. Rising electricity consumption requires adding new generation plants to meet peak loads and maintain reserve margins against unexpected surges. However, peak demand typically occurs for less than 5% of the annual operating hours. Consequently, certain generating units function only during these high-demand periods, often operating well below their full potential. Implementing active demand-side management at the distribution level—through demand response programs and VVO techniques—can effectively lower peak loads across the broader power system. This reduces the need for substantial investments in new generation, transmission, and distribution infrastructure. Traditionally, load tap changers (LTCs) on transformers and voltage regulators (VR) tap changers have addressed voltage fluctuations, while switched capacitors (CAPs) have managed reactive power flows, typically via timer-based or open-loop mechanisms.

In recent years, voltage regulation has become increasingly important as distributed renewable energy resources have become more integrated. Conventional voltage control equipment struggles to respond swiftly to transient disturbances and the variable output of renewables. In contrast, power electronics in photovoltaic (PV) inverters enable rapid adjustments, effectively managing the variability and uncertainty stemming from weather-dependent generation. A multi-agent system (MAS) for distributed control, featuring synchronized timing between voltage regulators and reactive power support from PV inverters, has been developed to create a collaborative voltage regulation scheme that mitigates issues arising from substantial PV penetration [1]. The objective is to reduce voltage swings and alleviate stress on traditional voltage-control infrastructure by leveraging the reactive power capacity inherent in PV inverters. Control actions involve adjusting tap settings on voltage regulators and modulating reactive power from PV inverters, aiming to minimize voltage deviations and reduce the frequency of operation of voltage regulators and capacitors [1, 2]. Investigations into current approaches and frameworks for decentralized voltage management in intelligent distribution grids are reviewed in the context of distributed architectures [3].

A separate investigation [4] proposes a coordination strategy based on fuzzy logic control (FLC) that integrates smart coordinated charging/discharging of plug-in electric vehicles (PEVs) within the distribution network under high PEV penetration, with an emphasis on iterative optimization procedures.

Rooftop photovoltaic (PV) installations are being incorporated into distribution networks at an accelerating rate [5–7]. This trend stems in part from the push to identify sustainable energy alternatives and broader environmental concerns related to climate change. Nevertheless, integrating renewable sources such as solar power into the grid can pose challenges unless carefully managed. At elevated penetration levels, uncoordinated PV systems may negatively impact node voltages due to overvoltage at connection points. Optimizing distribution system performance is therefore essential to accommodate these developments. A heuristic evolutionary algorithm serves as a validation tool in this context [5]. Traditionally, voltage and var control (VVC) methods have been applied for distribution-level voltage management. With the inclusion of PV generation and active demand dynamics, the framework has evolved into voltage, VAR, and watt (VVWO) optimization [6]. Centralized control of the distribution network is examined by Alboaouh [7], where an initial solution employs a metaheuristic technique, followed by exploration of an analytical approach to enhance system performance with PV integration [7]. In this dissertation, the volt-var-watt optimization problem is reformulated as a convex optimization task to guarantee attainment of the global optimum through analytical means, thereby validating the heuristic outcomes [7]. The reactive power support capabilities of voltage-source inverters in PV installations can be harnessed in distribution systems as a cost-effective alternative to constructing high-cost grid reinforcements. A building-integrated photovoltaic (BIPV) setup with three-phase grid interconnection is employed [8] to stabilize system voltage and enhance overall power factor.

The problem's objectives, decision variables, and constraints are reviewed, along with a detailed examination of the diverse approaches developed over time to address this challenge [9]. The wide array of solution techniques highlights

the inherent complexity in solving the VVO problem both effectively and efficiently. While classical optimization methods have proven to be efficient, dependable, quick, and relatively straightforward to code, they exhibit notable limitations when applied to VVO. Key shortcomings include difficulties with managing discrete variables and inequality constraints, as well as issues with convergence behavior and the guarantee of global optimality. In contrast, heuristic optimization methods offer distinct benefits compared to traditional approaches. These include enhanced global exploration capabilities, the potential to reach global convergence and optimality irrespective of problem formulation, and a natural suitability for handling discrete variables. However, their heuristic nature imposes primary limitations: higher computational demands and a strong dependence on proper parameter tuning for optimal performance and speed.

An optimal voltage regulation strategy for distribution systems with substantial renewable penetration is introduced in Liu et al. [10], employing the Deep Deterministic Policy Gradient (DDPG) algorithm. This involves placing distributed generation (DG) at each node and optimizing the voltage profile to keep it within specified upper and lower bounds [10]. Another study [11] explores a volt-var optimization framework to enhance voltage quality and reduce active power losses amid high DER penetration. It adopts a twin delayed approach in deep reinforcement learning—differing from prior voltage control efforts—by leveraging the reactive power outputs of multiple PV systems and battery energy storage systems (BESSs), as well as the active power output from BESSs [11]. In Shi et al. [12], a stability constraint is incorporated into reinforcement learning to ensure reliable real-time voltage regulation and maintain system stability [12].

In the present study, a supervisory, centrally coordinated control scheme is developed for volt-var optimization, incorporating integration of a PV-based microgrid with the primary distribution network. Various scenarios are investigated to illustrate the impact of microgrid integration on the VVO performance. These scenarios include: (1) Microgrid connected on-grid, with full control and coordination implemented in Matlab, (2) Microgrid connected on-grid but operated in a conventional decentralized local manner without coordination, serving as the base case with microgrid, (3) Microgrid in off-grid mode, with all control and coordination executed on the Matlab platform, and (4) Microgrid disconnected (off), with conventional local control applied without coordination. Scenarios 3 and 4 align closely with prior works [13, 14] that lacked microgrid integration, featuring local versus coordinated control, yet incorporate a metaheuristic optimization algorithm here. Subsequently, a comparative analysis is presented among these four scenarios and findings from earlier studies. The optimization is addressed through a harmony search metaheuristic method that accommodates integer, discrete, and continuous control variables. The proposed approach is shown to be computationally efficient. It supports applications in both operational and planning contexts. Results indicate that coordinating volt-var control devices yields substantial advantages in reducing active power losses, active power demand, and voltage fluctuations. Additionally, coordinated microgrid integration helps smooth peak demand profiles.

Volt-Var Control and Optimization

Volt-var optimization involves the most effective management of voltage magnitudes and reactive power flows to enhance distribution grid performance, achieved by reducing system losses, peak loads, overall energy use, or a combination of these. It relies on real-time data from the grid, gathered via sensors, smart meters, and SCADA infrastructure. Figure 1 illustrates the VVC devices typically employed in a distribution system, as presented in Uluski [15].

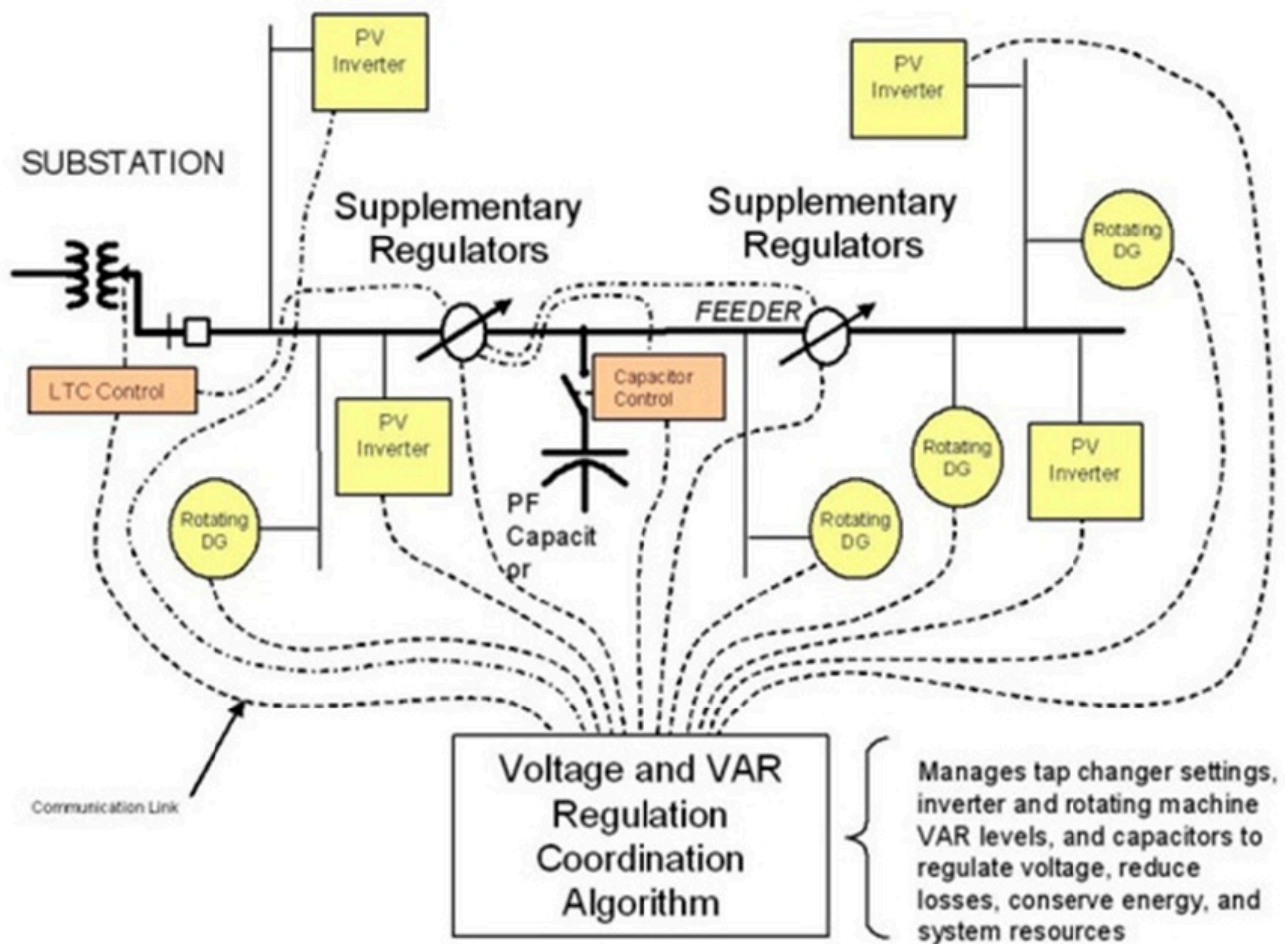


Figure 1. Volt-var devices on a distribution system [15].

There is no coordination among the voltage control devices, as they are generally managed independently by local controllers—for instance, switchable capacitors, voltage regulators, and on-load tap changer (LTC) transformers. The proposed method aims to coordinate voltage regulators (VRs) and capacitor banks (CAPs) to sustain optimal volt-var control (VVC) performance, even in distribution systems subject to rapidly varying operating conditions, such as high penetration of distributed generators (DGs).

VVO seeks to minimize power losses on a distribution feeder or reduce the total MW demand supplied by the substation. The decision variables include the tap positions of voltage-regulation devices and the on/off states of capacitor banks. The joint optimization of voltage and reactive power encounters two core difficulties:

1. Precise representation of the distribution system's response under any possible control action.
2. A robust and efficient optimization search method capable of delivering discrete solutions for the tap settings of voltage regulators and the switching status of capacitor banks. A robust VVO solution framework must be able to handle large-scale, realistic distribution networks exhibiting any of these characteristics.

VVO constitutes a nonlinear combinatorial optimization problem with the following primary attributes:

- Tap positions of regulating transformers and switching states of capacitor banks are integer variables.

- System demand and power losses are implicit functions of the control actions, which in turn depend on continuous (real-valued) decision variables within a nonlinear objective.
- The multiphase system model includes thousands of power flow equations subject to high-dimensional nonlinear constraints.
- The objective function and feasible solution set are non-convex.
- A high number of control variables exist within a large-dimensional search space.

Developing an effective search algorithm for mixed-integer nonlinear non-convex (MINLP-NC) problems remains highly challenging. A high-quality algorithm should be able to locate the global optimum or a solution very close to it.

Volt-Var Control and Optimization Problem Formulation

An integrated modeling approach is adopted for problem formulation. Switchable capacitor banks, voltage regulators, and the active and reactive power outputs of smart inverters—dependent on solar irradiance levels from PV generation—are included in the power flow analysis to evaluate the effects of changes in the status of these regulating devices on overall distribution system behavior. The proposed strategy focuses on voltage regulation and power-loss minimization through coordinated control of these devices. Per ANSI C84.1, the purpose of VVC is to maintain node voltages along the feeder within acceptable limits under all loading conditions [16]. LTCs and VRs typically allow voltage adjustment of up to 10% across 16 discrete steps [17]. Usually, only single-phase voltage is monitored, yet the LTC's operation at the substation affects all three phases. Voltage regulators operate similarly but are often configured to regulate each phase independently and may be located at various points along the feeder. At the same time, incorporating power loss minimization and limiting voltage deviations—while avoiding excessive operational wear from frequent tap operations and capacitor switching that could shorten device lifespan—transforms the VVC task into an optimization problem. Consequently, VVO can be expressed as a control and optimization problem in the form of Eqs.1–3:

$$\min (f(x) = P_{loss} = P_{gen} - P_{load}) \quad (1)$$

$$P_{gen} = P_{GRID} + \sum_{i=1}^k P_{PVi} \quad (2)$$

Subject to:

$$\begin{aligned}
 g_i(x, u) &= 0 & i &= 1 \dots n \\
 h_k(x, u) &\leq 0 & i &= 1 \dots k \\
 V_i^{\min} &\leq V_i \leq V_i^{\max} \\
 0.95 &\leq V_i \leq 1.05 \\
 0 &\leq u_{cap} \leq 1 \\
 -16 &\leq u_{tap} \leq 16 \\
 I_{microgrid}^{\min} &\leq u_{Imicrogrid} \leq I_{microgrid}^{\max} \\
 0 &\leq I_{1,microgrid} \leq 219.97 \\
 0 &\leq I_{2,microgrid} \leq 65 \\
 0 &\leq I_{3,microgrid} \leq 169.12
 \end{aligned} \tag{3}$$

This VVC problem must be solved for each feeder at every control update interval (which may be 1 minute, 5 minutes, or 1 hour), with the resulting updated device settings communicated to the local controllers. Because the control vector u includes both discrete and continuous variables from the microgrid, the problem becomes a computationally intensive, nonlinear, mixed-integer, combinatorial optimization task.

Binary variables are employed to represent the on/off status of switched capacitor banks; thus, the search vector for capacitor control u is structured as follows [Eq. 4](#):

$$\begin{aligned}
 u_{capi} &= [0, 1] \\
 u1_{cap} &= [u_{cap1}, u_{cap2}, u_{cap3}, \dots, u_{capl}] \tag{4} \\
 combination1 &= 2^l
 \end{aligned}$$

Where l is the total number of reactive power sources/capacitor banks, $i = 0, \dots, l$.

Tap positions for LTCs and VRs are represented as integer values and typically offer 32 possible positions. In this case, each tap step corresponds to 0.00625 per unit (p.u.) voltage change. Consequently, each tap adjustment on a VR results in a real-valued voltage increase or decrease of $0.00625 \times \text{tap p.u.}$ When a voltage regulation device has 32 discrete tap settings, and multiple such devices are present in the system, the total number of possible tap combinations becomes extremely large. For instance, even with only one three-phase LTC and three single-phase VRs ($m = 4$), there are 1,048,576 possible combinations.

$$\begin{aligned}
 -16 &\leq tap \leq 16 \\
 u_{LTC/VR} &= [u_{LTC}, u_{VR1}, u_{VR2}, \dots, u_{VRm}] \\
 u_{tapi} &= [-16, -15, -14, \dots, 0, \dots, 14, 15, 16] \\
 u_{2tap} &= [u_{tap1}, u_{tap2}, u_{tap3}, \dots, u_{tapm}] \\
 combination2 &= 32^m
 \end{aligned} \tag{5}$$

Where m is the total number of tap-changing units (VRs and LTCs), with $i = 0, \dots, m$.

The control variables from the microgrid include the current sources $I_{Sources}$, I_1 , I_2 , and I_3 .

$$\begin{aligned}
 u_{3I} &= [I_{1,microgrid}, I_{2,microgrid}, I_{3,microgrid}] \\
 combination3 &= 3^n
 \end{aligned} \tag{6}$$

$$\begin{aligned}
 TotalCombination &= combination1 * combination2 * combination3 \\
 TotalCombination &= 2^2 * 32^4 * 3^1 = 12,582,912
 \end{aligned} \tag{7}$$

The expression for the total number of feasible combinations is provided in [Eq. 7](#). For a system containing only two capacitor banks, four tap-changing devices, and one microgrid with three current sources, the number of possible combinations reaches 12,582,912. It is clear that as the system scale and the quantity of control devices increase, the required number of power flow evaluations grows dramatically. In combinatorial optimization problems, the problem complexity grows exponentially with the number of decision variables (to the power of their respective factors). Consequently, attempting to determine the global optimal device settings via exhaustive deterministic search (brute-force) becomes computationally prohibitive in terms of both processing time and resource demands. To obtain the true global optimum—or a solution very close to it—alternative computational strategies may be required, as explored in previous studies [\[13, 14\]](#), or metaheuristic algorithms may be applied. In the present work, the harmony search (HS) algorithm is selected as the metaheuristic solver for the optimization problem. The HS algorithm is motivated by the process through which musicians improvise to achieve pleasing harmony: they experiment with different combinations of musical pitches (discrete variables) drawn from their memory. This pursuit of an ideal harmony closely parallels the search for optimal solutions in engineering optimization tasks. The HS algorithm, inspired by the principles of musical improvisation, excels particularly at problems involving discrete decisions (such as capacitor bank scheduling or tap position optimization) and can effectively manage both discrete and continuous variables.

The complete vector of decision variables (or control variables), denoted x , which encompasses all integer values for capacitor bank states and tap positions, along with real-valued variables representing the microgrid current injections (I_{Source} , or equivalently PPV and QPV), is formulated for the entire problem as shown in [Eq. 8](#).

$$\begin{aligned}
 x &= [u_{cap}, u_{LTC/VR}, u_{I,microgrid}] \\
 x &= [u_{cap1}, u_{cap2}, u_{LTC}, u_{VR1}, u_{VR2}, u_{VR3}, u_{I1,microgrid}, u_{I2,microgrid}, u_{I3,microgrid}]
 \end{aligned} \tag{8}$$

Harmony Search Algorithm

Metaheuristic algorithms play a vital role in computational intelligence for addressing complex, difficult-to-solve problems. The harmony search (HS) algorithm is a population-based, iterative metaheuristic technique inspired by the musical process of searching for the most aesthetically pleasing harmony [18, 19]. It mimics the way a musical ensemble improvises to produce the most harmonious composition. In the same way that the quality of each musical note contributes to the overall aesthetic appeal of the harmony, the fitness value of decision variables determines the quality of a candidate solution in optimization.

- When all notes combine to form a beautiful harmony, musicians store that successful experience in memory, increasing the likelihood of producing even better harmonies in future improvisations.
- Similarly, in optimization, an initial set of random solutions is generated from decision variables within their allowable ranges;
- If the objective function values of these solutions are promising, there is a higher probability that subsequent iterations will yield improved or successful outcomes.

The key parameters of the HS algorithm include:

- Harmony memory (HM) matrix, which stores the set of initial candidate solutions (population).
- Harmony memory size (HMS).
- Harmony memory consideration rate (HMCR): an improvisation parameter that determines the probability of selecting a value for a variable in a new candidate solution from the existing entries in the HM matrix.
- Pitch adjustment rate (PAR): another improvisation parameter that controls the likelihood of slightly perturbing (tuning) a selected value from the HM to a neighboring value.
- Maximum number of improvisations (MaxImp), representing the total number of iterations.

The algorithm performs three primary operations: harmony memory consideration, pitch adjustment, and randomization.

When constructing a new harmony, the probability of selecting a value directly from the HM matrix is denoted E1, the probability of applying pitch adjustment is E2, and the probability of random selection is E3:

$$\begin{aligned} & x_{new}(i) \\ & : p(E_1) \\ & = HMCR * (1 - PAR) \quad (\text{a note in memory}) \end{aligned}$$

$$\begin{aligned} & x_{new}(i) \\ & : p(E_2) \\ & = HMCR * PAR \quad (\text{adjacent to the note in its memory}) \end{aligned}$$

$$\begin{aligned} & x_{new}(i) \\ & : p(E_3) \\ & = 1 - HMCR \quad (\text{randomly choose}) \end{aligned}$$

The HS algorithm stands out as a robust and effective technique for tackling systems characterized by unpredictability and uncertainty, demonstrating strong capability for managing both linear and nonlinear problems, as well as mixtures of continuous and discrete variables, with superior performance.

The principal steps of the harmony search (HS) algorithm are outlined as follows:

Step 1: Initialization of the algorithm parameters.

Definition of the optimization problem's control variables—specifically, the tap positions of transformers and voltage regulators ($u_{LTC/VR}$) and the on/off states of switchable capacitors (u_{cap}) along with their respective search spaces. These are initialized through random generation followed by appropriate integer adjustments where required.

Step 2: Construction of the harmony memory (HM) matrix.

This is achieved by uniformly selecting values within the defined ranges of the control variables for the optimization problem.

Next, the objective function $f(x)$ (representing the fitness value) is evaluated for each candidate solution vector in the initial population.

The harmony memory matrix, containing the starting candidate solutions, the corresponding fitness vector, and the HS algorithm parameters, is established as follows:

$$HM = \begin{pmatrix} x_{11} & \dots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{HMS1} & \dots & x_{HMSn} \end{pmatrix} \quad (9)$$

$$f(x) = \begin{pmatrix} f1 \\ \cdot \\ \cdot \\ \cdot \\ f_{HMS} \end{pmatrix} \quad (10)$$

The HS algorithm parameters are configured as:

- HSparams.HMS = 9 to 90;
- HSparams.MaxImp = 1000 to 10,000;
- HSparams.HMCR = 0.9;
- HSparams.PAR = 0.3;
- HSparams.b = $(x_U - x_L)/100$.

Step 3: Improvisation of a new harmony.

This phase involves the core improvisation process (including pitch adjustment and randomization): each component of a harmony vector can be determined through one of three mechanisms, governed by the HMCR, PAR, and the remaining probability ($1 - \text{HMCR}$) for pure randomization.

```

If      r1      <      HMCR      then
Create  a      random  solution  candidate  vector.
else
    Create a solution candidate vector such that
    For    each    column    in    HM,    do
        Randomly    pick    an    element
        Create      a      random      number      r2
        If          r2          <          PAR          then
            With PAR probability perturb this element
            This    perturbation    is    +/-    1
        end
    end
end
end
end

```

Algorithm 1. Steps to generate a new candidate solution vector.

Step 4: Evaluation of the fitness value for the newly improvised candidate solution.

The new solution is then compared with the worst-performing harmony currently stored in the HM matrix. If the new candidate demonstrates better fitness than the worst entry, the worst harmony is replaced by this improved solution.

Step 5: The process returns to Step 3, repeating Steps 3 and 4 iteratively until a predefined termination criterion is satisfied—such as achieving the desired level of solution accuracy or reaching the maximum allowable number of improvisations (MaxImp).

Computational Complexity of the Search Algorithms

HS algorithm

The computational complexity of the harmony search (HS) algorithm is determined primarily by the number of decision variables (control devices), the population size, and the total number of iterations. The following provides a detailed breakdown:

Notation

- N = Number of decision variables (control devices), equivalent to the problem dimension;
- HMS = Harmony Memory Size (population size);
- $MaxImp$ = Number of iterations;
- $f(x)$ = Time complexity required for a single fitness function evaluation (including power loss computation and power flow equations).

Complexity breakdown

Initialization:

- A set of HMS harmonies (candidate solutions) is generated randomly;
- Each harmony comprises N decision variables;
- Complexity: $O(HMS \times N)$.

Improvisation (New Solution Generation):

- In every iteration, one new candidate solution is constructed by drawing values from the harmony memory, with possible pitch adjustment or random selection;
- This process scales linearly with the dimension: $O(N)$.

Fitness Evaluation:

- The newly generated solution undergoes evaluation via the objective function;
- The complexity is dictated by the cost of $f(x)$;
- In the context of volt-var optimization, $f(x)$ encompasses power flow computations, whose complexity ranges from $O(N^2)$ to $O(N^3)$, depending on the chosen solver (e.g., Newton–Raphson, Newton–Raphson with Jacobian matrix, Gauss–Seidel, among others).

Memory Update:

- If the new solution outperforms the current worst harmony in the memory, it replaces that worst entry;
- This involves comparing the new fitness value against existing ones;
- Complexity: $O(HMS)$.

Total Complexity per Iteration:

$$O(N + f(x) + HMS)$$

For MaxImp iterations, the overall complexity becomes:

$$O(\text{MaxImp} \times (N + f(x) + \text{HMS})).$$

Worst-case complexity in volt-var optimization

When power flow calculations dominate and exhibit $O(N^2)$ or $O(N^3)$ complexity, the total complexity simplifies to

$$O(\text{MaxImp} \times (N + N^2 + \text{HMS})) \text{ or } O(\text{MaxImp} \times (N + N^3 + \text{HMS})), \text{ which remains polynomial in nature.}$$

Brute force

General formula for brute force complexity

In a brute-force (exhaustive) search, every feasible combination of variable settings is evaluated. The total number of evaluations equals D^N , where

D = average number of possible discrete values per control variable.

Thus, the overall computational complexity is

$$O(D^N \times f(x)),$$

where

- N = Number of control variables;
- D = Number of discrete choices per variable;
- $f(x)$ = Computational cost of evaluating one candidate solution (fitness function).

Complexity in volt-var optimization

Within volt-var optimization, the decision variables consist of

- Capacitor bank switching states (discrete);
- Transformer tap positions (discrete);
- Reactive power outputs (continuous or discrete);
- Other voltage regulation devices (discrete);
- Continuous variables from power flow equations;
- Current injections from distributed energy resources (DERs) (continuous).

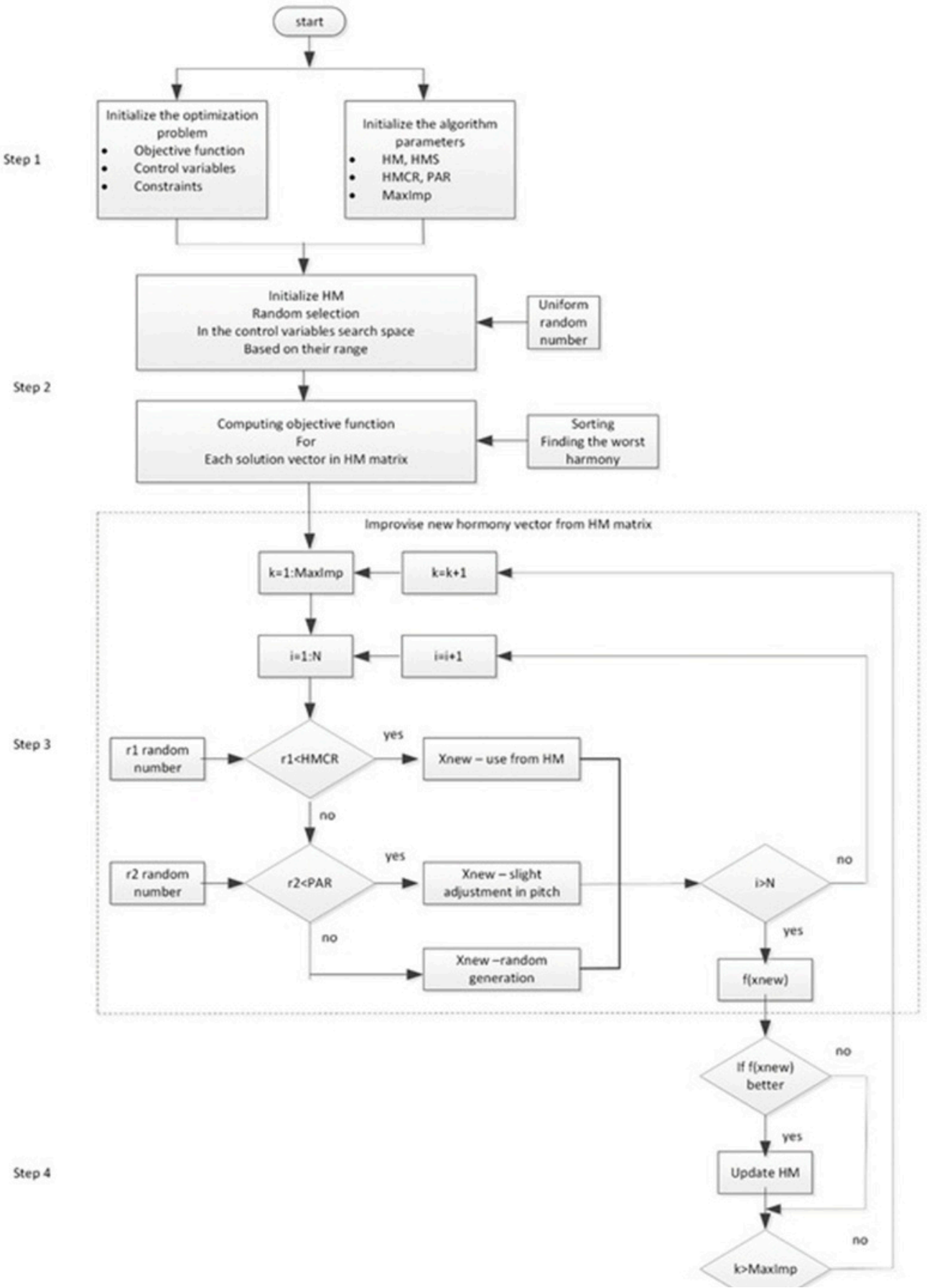
For a system involving N control devices, each with D possible settings, combined with power flow analysis costing $O(N^2)$ or $O(N^3)$ per evaluation, the brute-force complexity escalates to

$$O(D^N \times N^2) \text{ or } O(D^N \times N^3), \text{ which is exponential in } N.$$

Due to this exponential scaling, brute-force enumeration becomes practically infeasible as the number of control variables increases. Previous studies [13, 14] employed brute force only within systematically reduced search spaces. In contrast, the HS algorithm is favored in this research for volt-var optimization because it consistently delivers near-optimal solutions while maintaining significantly lower computational complexity.

Coordinated Control of Volt-Var Optimization with HS Algorithm

Figure 2 illustrates the flowchart outlining the proposed solution procedure for achieving coordination and optimization of the volt-var problem through application of the harmony search (HS) algorithm.



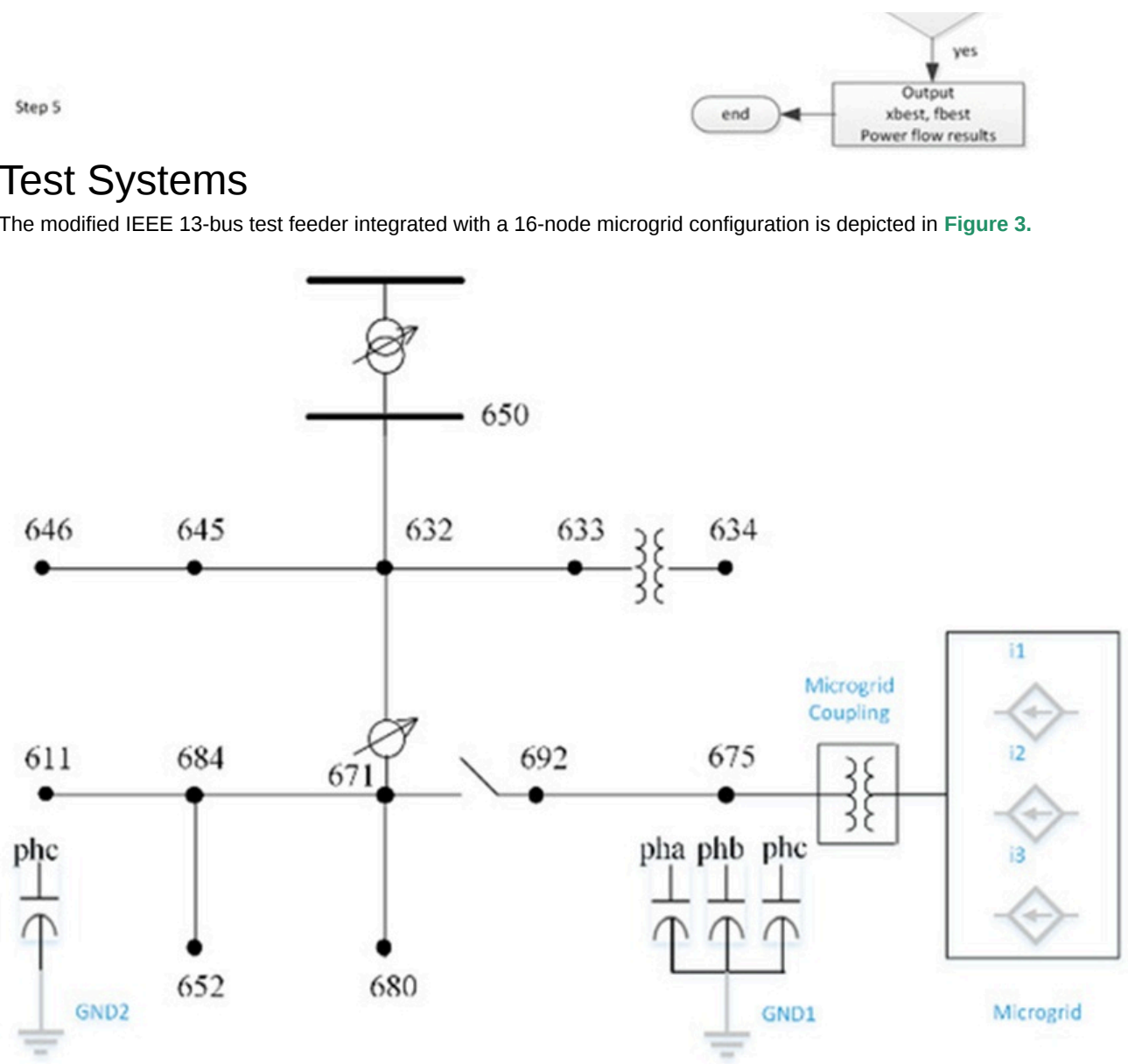


Figure 3. Modified IEEE 13-bus test feeder incorporating a microgrid with three current sources (I sources).

In addressing the VVC/VVO problem, the objective is to optimize reactive power flow while maintaining voltage regulation in electric power distribution networks. The VVC component handles real-time voltage adjustment and reactive power management through the use of voltage regulators (VRs) and on-load tap changers (OLTCs) for voltage control, capacitor banks for reactive power compensation, and distributed energy resources (DERs) for both active and reactive power contributions. The VVO component emphasizes minimizing power and energy losses, enhancing overall system efficiency, reducing and smoothing peak demand, and adhering strictly to the voltage limits prescribed by regulatory standards.

Table 1 details the locations of the control variables—expressed in OpenDSS notation—along with their respective allowable ranges for the test circuit.

Table 1. Control variables (encompassing voltage regulation, reactive power compensation, and active/reactive power devices).

Control variables	Location (Bus No.)	Ranges
LTC	650.1.2.3–RG60.1.2.3	–16, –15, ..., 15, 16
VR, reg1, (ph a)	670.1–671.1	–16, –15, ..., 15, 16
VR, reg2, (ph b)	670.2–671.2	–16, –15, ..., 15, 16
VR, reg3, (ph c)	670.3–671.3	–16, –15, ..., 15, 16
CAP, cap1	675.1.2.3	600 kVar
CAP, cap2	611.3	100 kVar
ISource, I1, microgrid	675.1	0, ..., 219.97 A
ISource, I2, microgrid	675.1	0, ..., 65 A
ISource, I3, microgrid	675.1	0, ..., 169.12 A

A representative daily load profile for the main distribution system and the corresponding PV generation profile, both sampled at 15-minute intervals, are presented in **Figure 4**. The top panel shows the load profile of the main grid, the middle panel displays the PV-based microgrid generation profile, and the bottom panel illustrates the net (aggregated) load shape resulting from their combination.

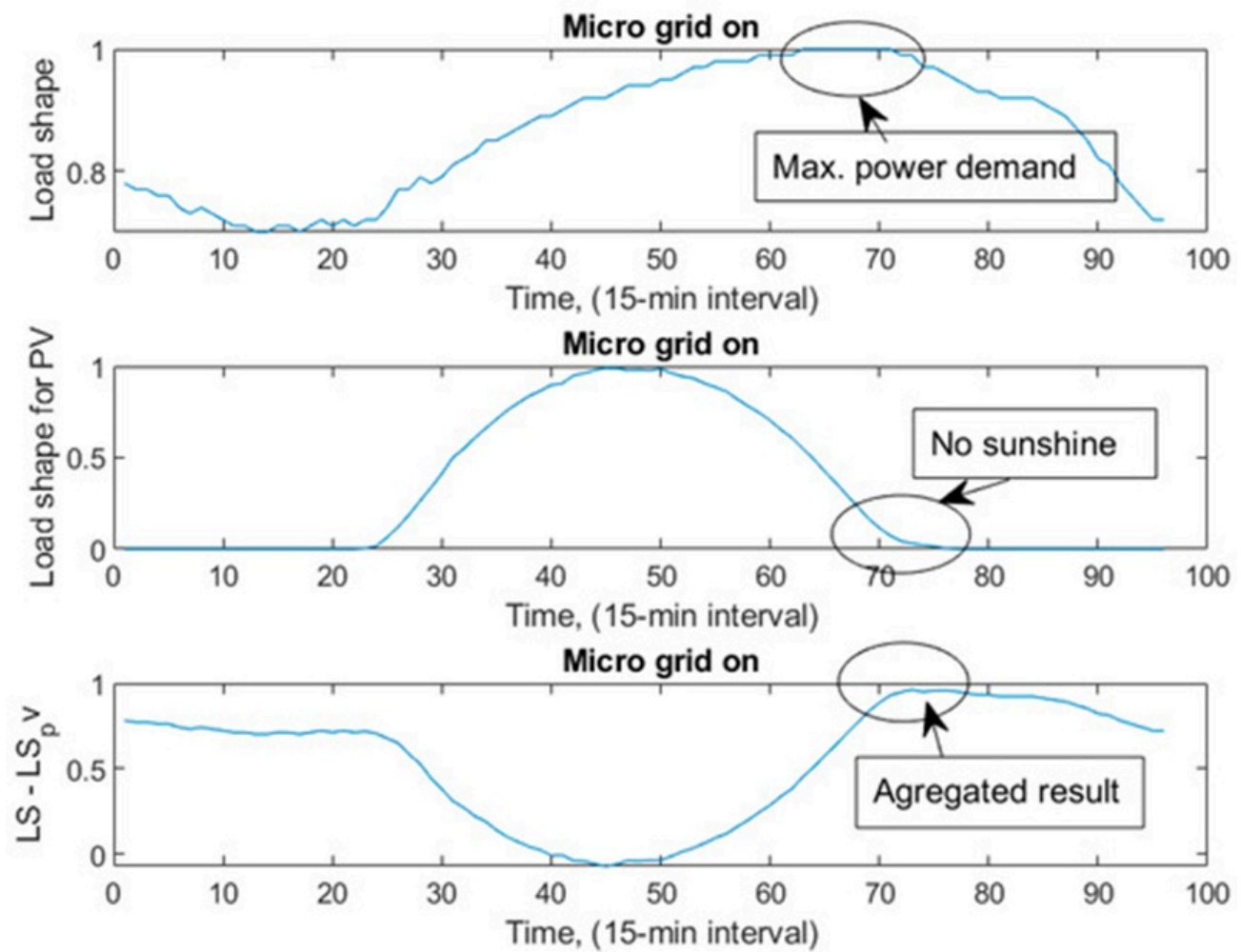


Figure 4. Load profiles: main grid, microgrid PV generation, and combined net demand.

In **Figure 4**, the main grid employs a modified IEEE 13-node test circuit load shape (denoted LS.mod2). The microgrid utilizes a dedicated PV load shape (LS_p). The resulting net daily demand curve, computed as $LS - LS_p$, exhibits the characteristic “duck curve” shape commonly associated with high solar penetration [20].

Simulations of unbalanced power flow are conducted in MATLAB™ using OpenDSS [21].

The microgrid model employed in this study is derived from an example included in the OpenDSS distribution package (last updated 20 November, 2019), based on the IEEE 13-bus test case. It demonstrates microgrid simulation using three current sources designated as ISource.

OpenDSS is an open-source distribution system simulator featuring a COM (Component Object Model) interface that facilitates modifying control algorithms, retrieving solution outputs, adjusting circuit parameters, and executing OpenDSS commands.

OpenDSS performs the core power flow computations, while MATLAB implements the control logic, monitors voltages and currents, and actuates devices based on the developed optimization algorithms. To prevent conflicts arising from simultaneous control attempts on the same elements, all native OpenDSS control blocks are disabled (set to off mode) [21].

The low-voltage bus of the substation transformer serves as the point of common coupling (PCC), where the microgrid electrically interfaces with the utility grid [22]. A block diagram illustrating the PV System element model is available in the OpenDSS reference manual [23].

To model Microgrid 3, three independent single-phase current sources (I sources) are incorporated, as illustrated in **Figure 3**. Due to the unbalanced distribution system, each current source is assigned a distinct magnitude. One of these sources tracks the irradiance profile to emulate photovoltaic generation. The PV load shape is originally recorded at 1500 points per day with 1-minute resolution; for consistency with the main grid load profile, simulation data are aggregated and resampled to 15-minute intervals.

Cases

Case 1: On-grid operation of microgrid, the microgrid is connected to the main grid: coordinated control

The microgrid is connected and operational. All control actions and coordination are executed entirely on the MATLAB platform.

In OpenDSS, daily load profiles for both the main grid and PV generation are disabled for the power flow solution, and the control mode is set to off for all regulators and capacitors. The MATLAB platform assumes full responsibility for the management and coordination of the devices.

Case 2: On-grid operation of microgrid, the microgrid is connected to the main grid: conventional control

The microgrid is connected and operational, but it operates under conventional local control without any coordination. This scenario serves as the base case.

In OpenDSS, the control mode is enabled (set to on) for regulators and capacitors. Load shapes for the grid demand and PV generation remain disabled. In MATLAB, loads and current sources are dynamically updated throughout the day based on their respective load shapes.

Case 3: Off-grid (islanded) operation of microgrid. the microgrid is separated from the main grid: coordinated control

The microgrid is disconnected and operates in islanded mode. All control and coordination tasks are handled exclusively on the MATLAB platform.

In OpenDSS, daily load profiles for grid demand and PV generation are disabled, and the control mode for regulators and capacitors is set to off. MATLAB manages each element's operation.

Case 4: Off-grid (islanded) operation of microgrid. the microgrid is separated from the main grid: conventional control

The microgrid is disconnected and operates in islanded mode, but under conventional local control without coordination. This scenario serves as the base case.

In OpenDSS, the control mode is enabled (set to on) for regulators and capacitors. Load shapes for grid demand and PV generation remain disabled. In MATLAB, loads and current sources are updated over the day in accordance with their

respective load shapes.

Detailed descriptions of the simulation setup and comparative analysis for each case are provided in the following section.

Results and Discussion

The harmony search (HS) algorithm was successfully implemented using MATLAB R2022b. The execution time for a full daily simulation pattern was recorded for both on-grid and off-grid microgrid configurations, as illustrated in [Figure 5](#).

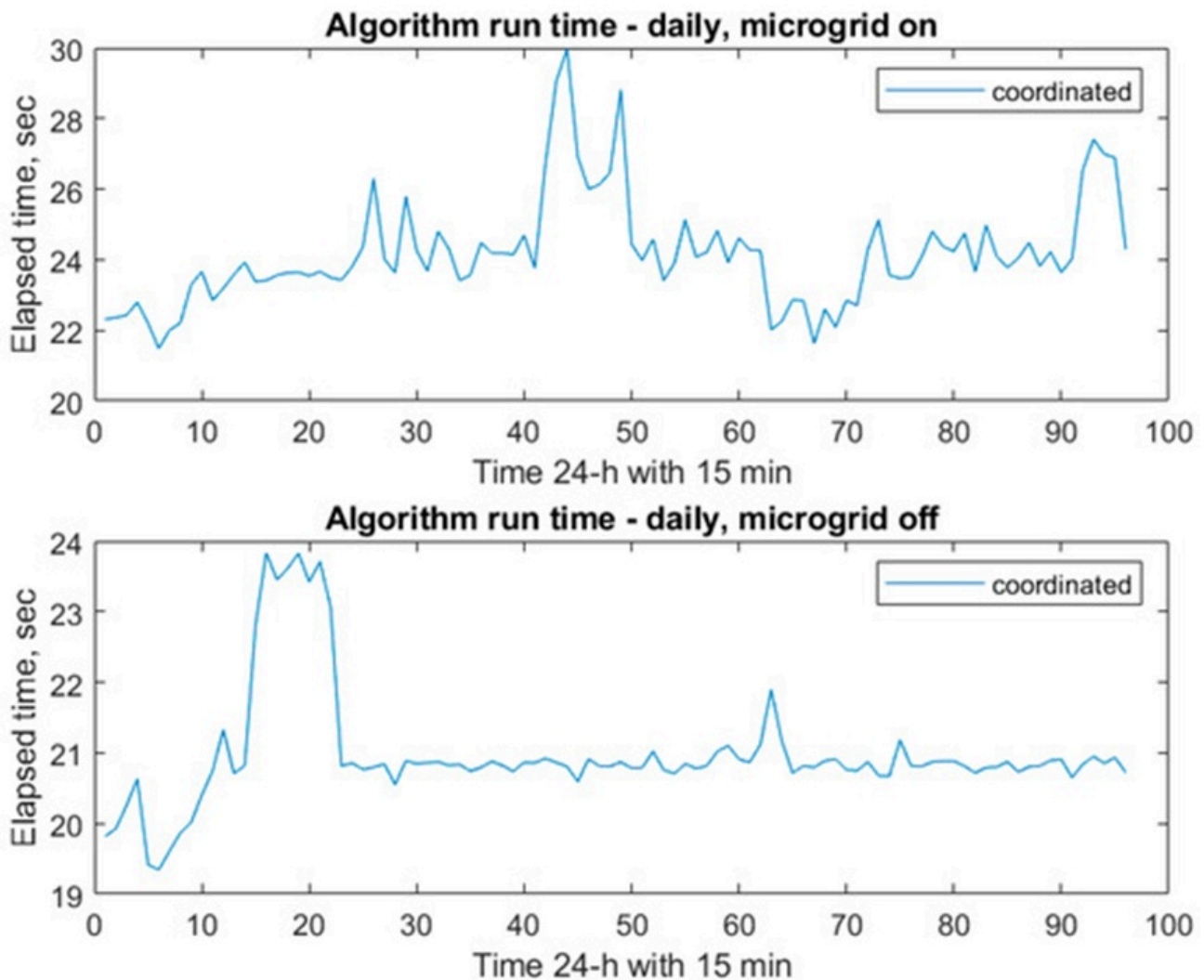


Figure 5. Algorithm execution time.

The simulations were performed on a computer with the following specifications:

Intel Core i7-8550U CPU @ 1.80 GHz, 16 GB RAM, 64-bit operating system.

As shown in [Figure 5](#), the computation time ranged from 19 to 30 seconds. Given this relatively short execution duration, the proposed approach is suitable for both planning studies and real-time operational applications.

Execution time exhibits greater variability during on-grid microgrid operation compared to off-grid scenarios, even under coordinated control. These fluctuations are likely attributable to the dynamic behavior of the PV inverter operation.

Figure 6 demonstrates the convergence behavior of the HS algorithm toward the optimal solution, minimizing active power losses. The algorithm was run for more than 5000 iterations to evaluate further improvement potential; however, in each trial, convergence stabilized by a maximum of 400 iterations with no additional gains observed. Thus, extending the number of iterations beyond this point would unnecessarily increase simulation time without meaningful benefit.

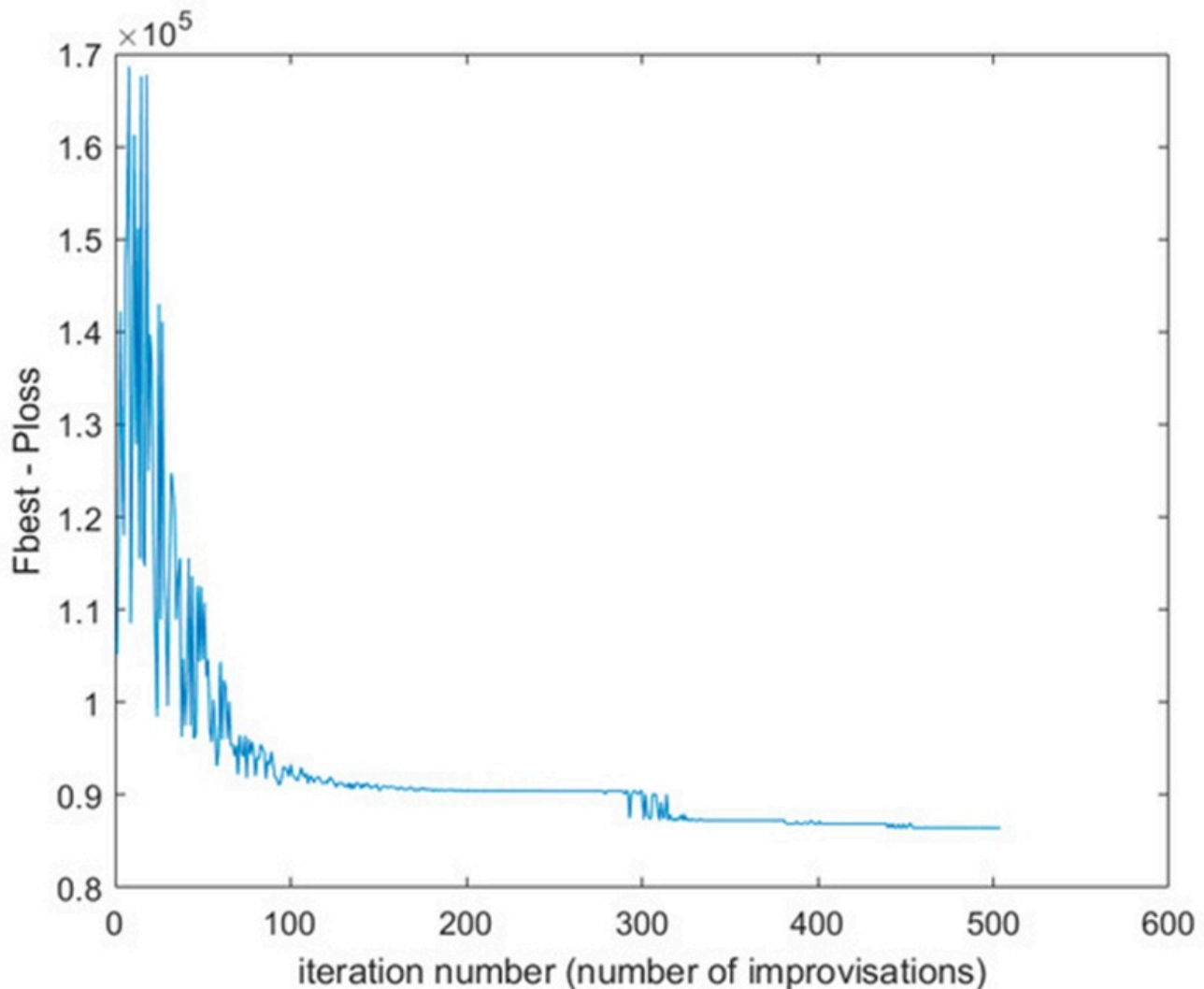


Figure 6. Example convergence profile of the HS algorithm.

Case 1: Microgrid is on-grid. all control and coordination are implemented in MATLAB

Referring to the net daily load shape in **Figure 4**, the demand drawn from the main grid reached its lowest levels around midday, coinciding with the microgrid's peak PV production. This resulted in a substantial reduction in overall active power losses (Ploss). The system effectively functioned as two independent sections during this period: the microgrid supplied sufficient current to serve the lower portion of the main grid load, eliminating the need for additional current from the upstream grid. This outcome validates the effectiveness of the proposed coordinated control strategy. The upper section of the circuit remained supplied by the IEEE 13-node test feeder, while the lower section was powered solely by the

microgrid. Consequently, current flow through the main grid was reduced, leading to lower peak demand, reduced active power demand, and decreased active power losses.

During the evening hours—specifically in the 15-minute intervals roughly between 65 and 75 (corresponding to approximately 4:15 PM to 7:15 PM)—power demand from the main grid increased noticeably, as depicted in Figure 4. This period was accompanied by adjustments in tap positions, as shown in Figure 7. Due to the unbalanced feeder load, tap settings varied across regulators: some increased, while others decreased, to maintain the target voltage levels. In particular, during these intervals, reg1 transitioned between taps 1 and 0; reg2 shifted among taps 1, 0, −1, and −2; and reg3 operated between taps 0 and −1.

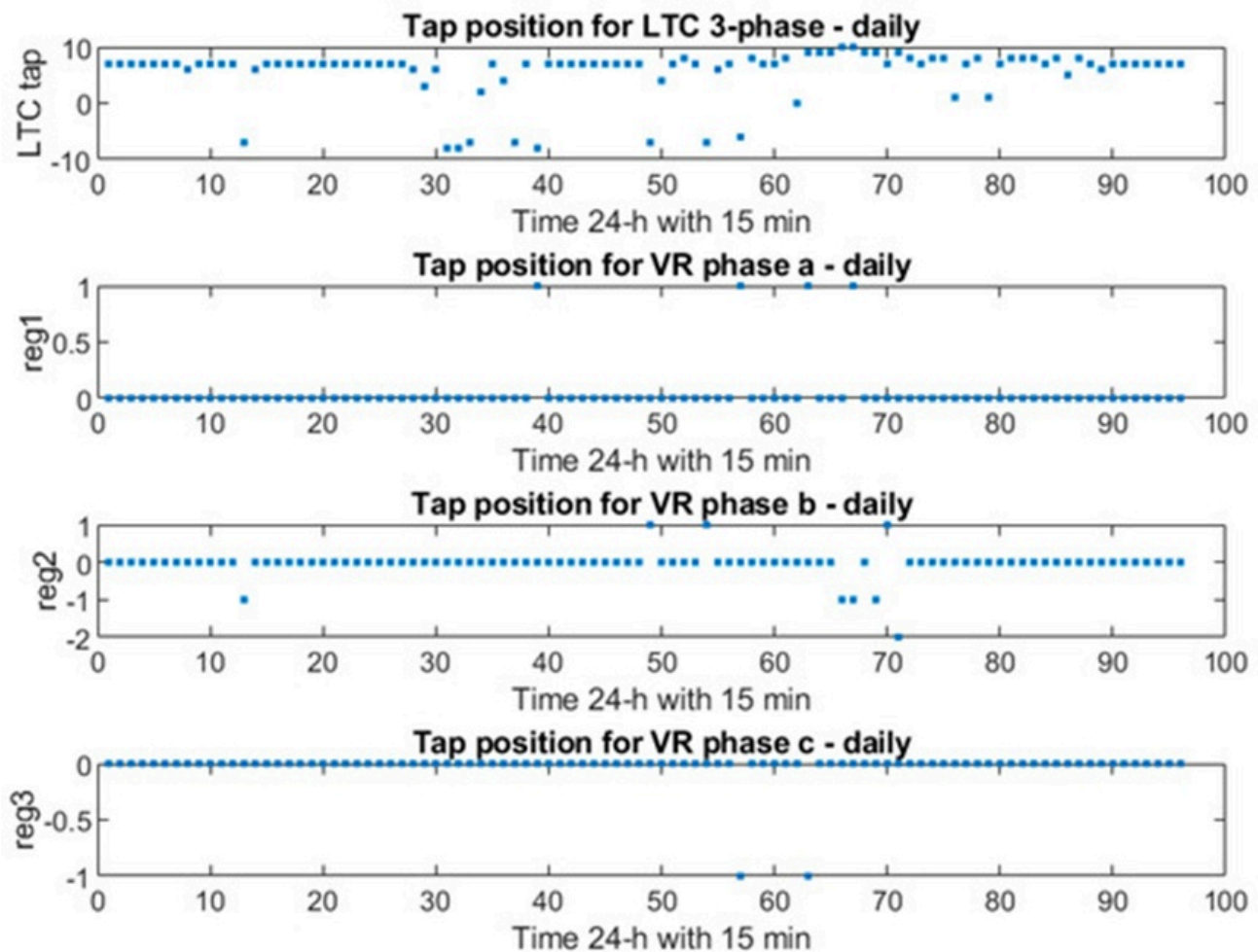


Figure 7. Tap positions of the LTC and VRs under coordinated control with the microgrid connected, a daily optimal profile.

Figure 7 shows that the tap positions of the three-phase LTC serving the main grid exhibited greater variation than those of the single-phase voltage regulators (VRs). Similar differences were noted between the single-phase units reg2 and reg3 and the three-phase unit reg1. Such discrepancies can also be attributed to unbalanced loading in certain sections of the feeder.

Both capacitor banks were activated (status on) during peak demand periods to supply the required reactive power at their respective connection points in the circuit, as illustrated in Figure 8.

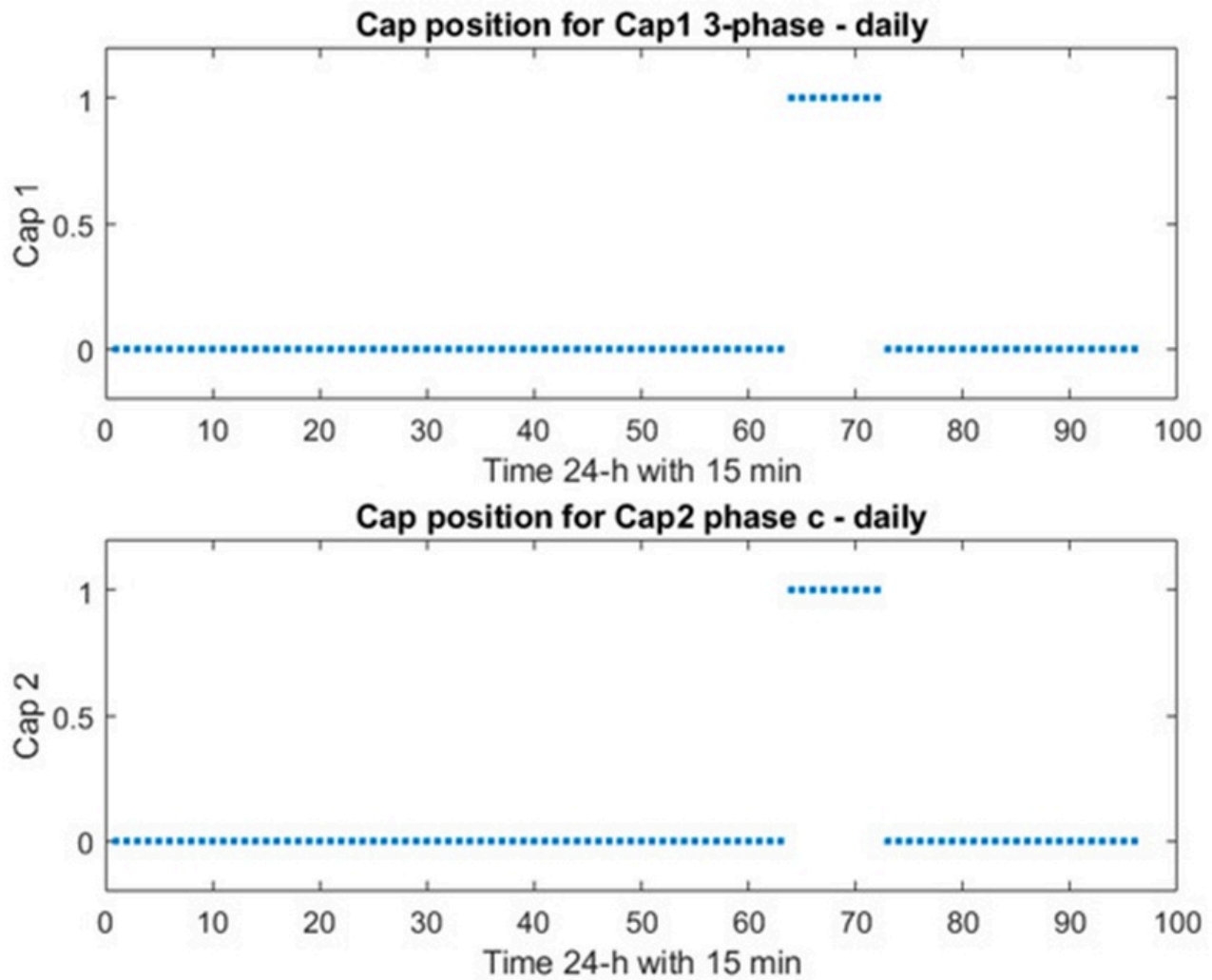


Figure 8. Capacitor bank statuses under coordinated control with the microgrid connected, a daily optimal profile.

Node voltage magnitudes began to increase, as depicted in [Figure 9](#). Thanks to the coordinated control strategy, voltage levels remained more stable and were generally confined within the acceptable range of 0.95 to 1.05 p.u., with fluctuations effectively minimized. Although occasional drops to around 0.9 p.u. occurred for phases A and B at a few isolated time steps, voltages stayed close to 1 p.u. throughout most of the day. As shown in [Figure 9](#), the highest voltage levels across all phases were recorded at bus 650, which corresponds to the location of the LTC connection in the test system ([Figure 3](#)). This pattern holds consistently across the remaining voltage profile figures.

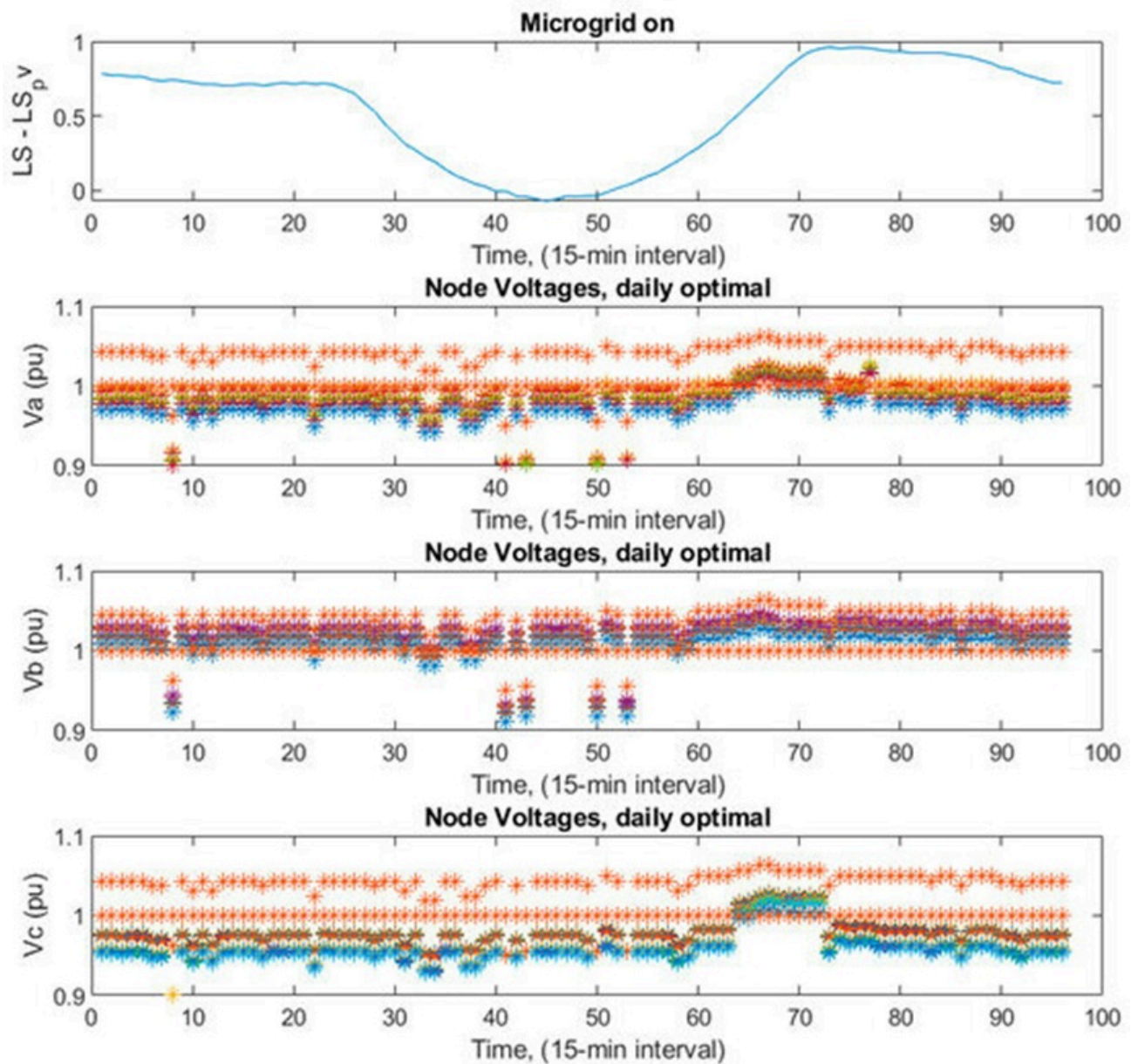


Figure 9. Daily voltage variations across 16 nodes under coordinated control with the microgrid connected.

During the evening hours—specifically in the time intervals approximately between 65 and 75 (corresponding to roughly 4:15 PM to 7:15 PM)—power demand from the main grid rose as PV generation (LS_{pv}) declined. As active power demand (P_{demand}) increased during these periods, the state variables closely tracked the overall daily load shape pattern, as observed in [Figures 10 and 11](#). In contrast, during most other periods of the day, the active power demand from the main grid, along with the microgrid's active, reactive, and apparent powers, remained notably smooth owing to the coordinated control approach.

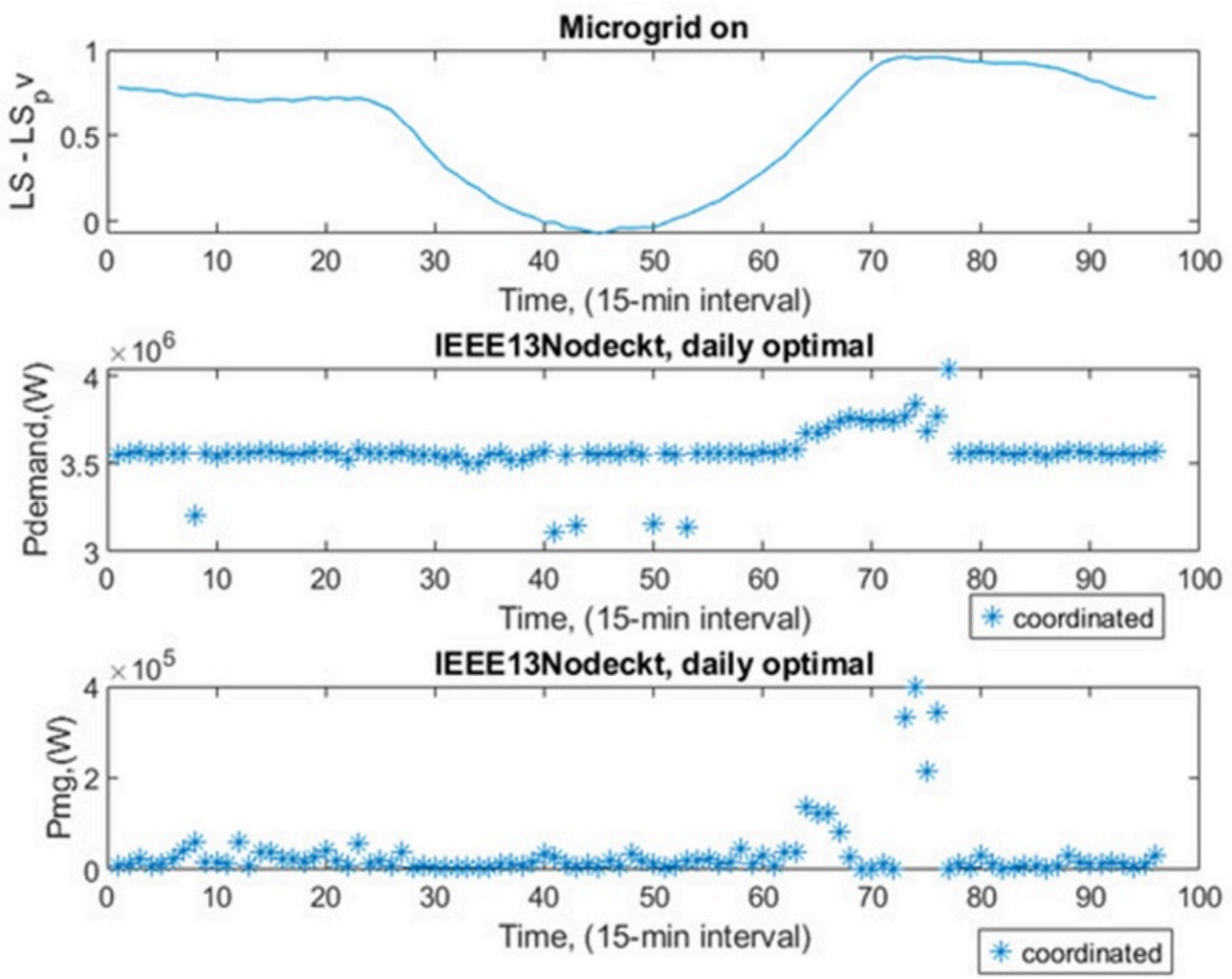


Figure 10. Active power demand of the main grid and active power output of the microgrid under coordinated control when the microgrid is connected.

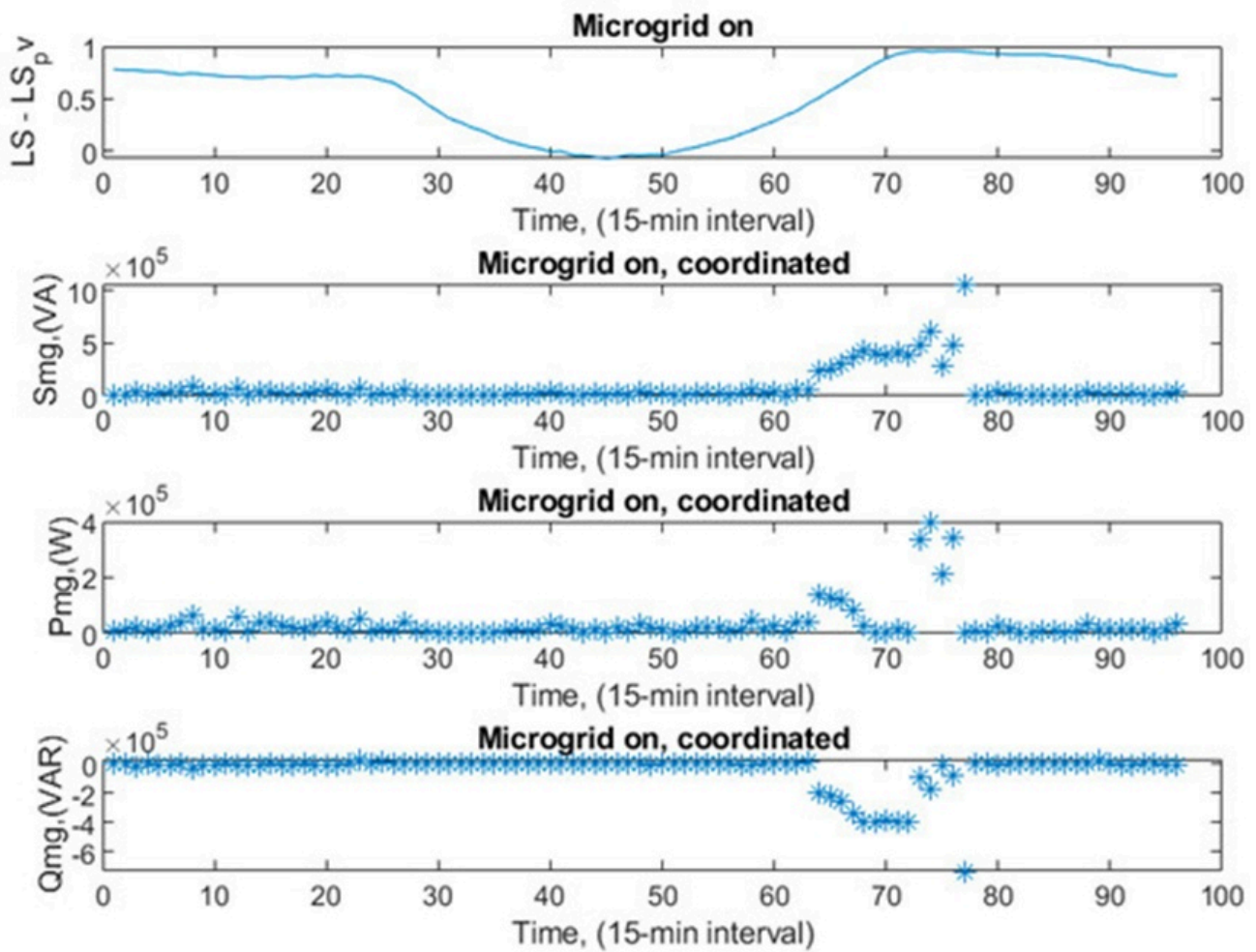


Figure 11. Apparent, active, and reactive power profiles of the microgrid under coordinated control, daily pattern.

Case 2: Microgrid is connected but operates under conventional local control without coordination. This scenario serves as the base case

For the power flow solution in OpenDSS, the control mode was enabled (set to on) for regulators and capacitors. Load shapes for the main grid demand and PV generation remained disabled. In the MATLAB environment, loads and current sources were updated throughout the day in accordance with their respective load profiles.

Figure 12 displays the tap settings under local control. In contrast to Case 1, which employed supervisory centralized coordination where the LTC varied between taps -10 and -10, here the LTC fluctuated between taps 8 and 9. This reflects local decision-making by an operator without full awareness of the overall circuit conditions. Consequently, reg1, reg2, and reg3 remained fixed at tap 16 throughout the day to satisfy localized voltage requirements.

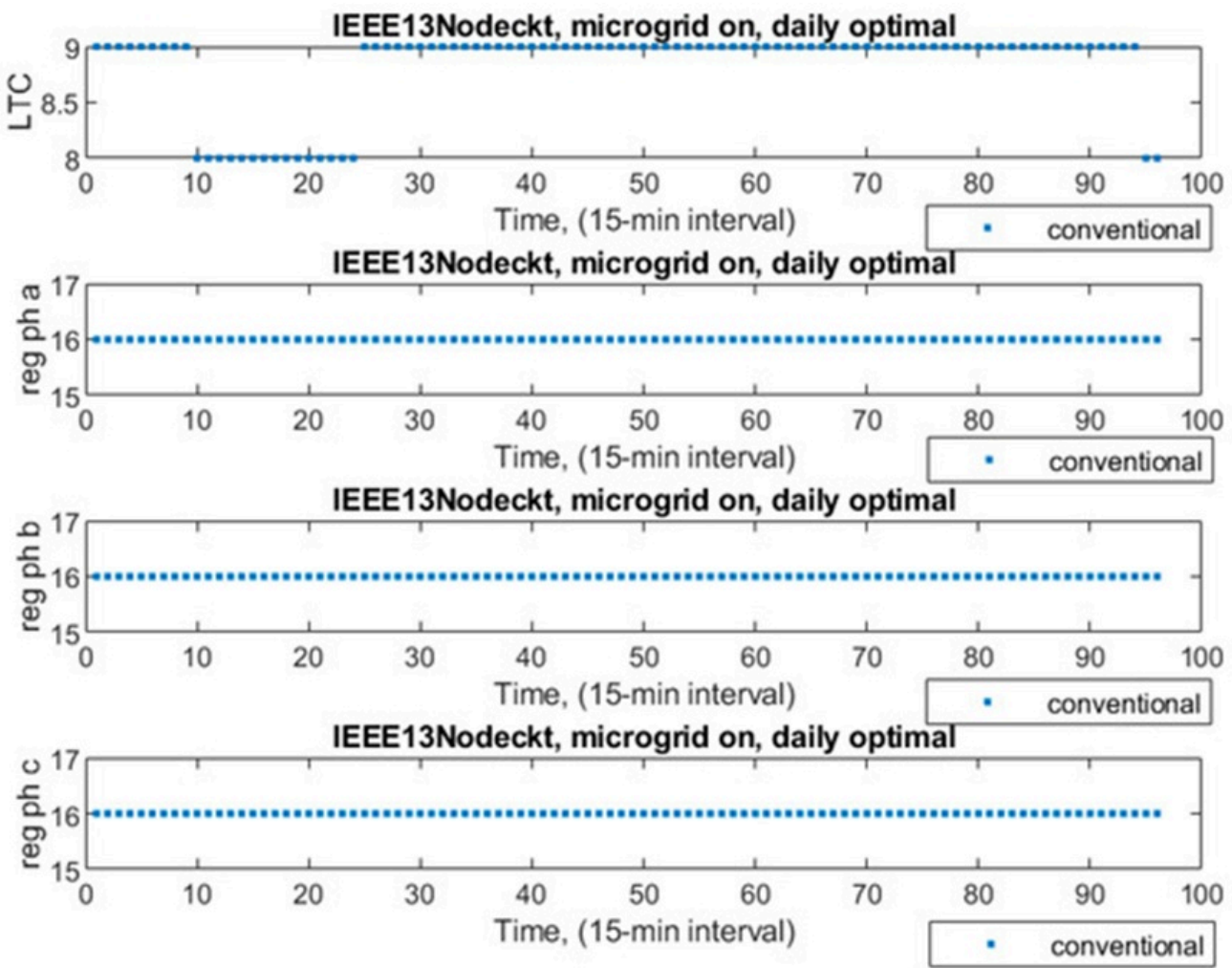


Figure 12. Tap positions of the LTC and VRs in the base case: conventional local control with the microgrid connected.

These tap positions for the VRs were substantially higher than those observed in Case 1, representing the maximum settings across all phases. Capacitor banks remained switched on (status 1) throughout the day, with no variation; therefore, figures for cap1 and cap2 are omitted. Owing to the elevated tap settings, node voltages were predominantly above 1 p.u., as shown in [Figure 13](#). Although voltages remained within acceptable limits, operating the system with values consistently near or above the upper threshold is undesirable. As a result, both the total active power demand and losses were higher than under the coordinated approach, as illustrated in [Figure 14](#).

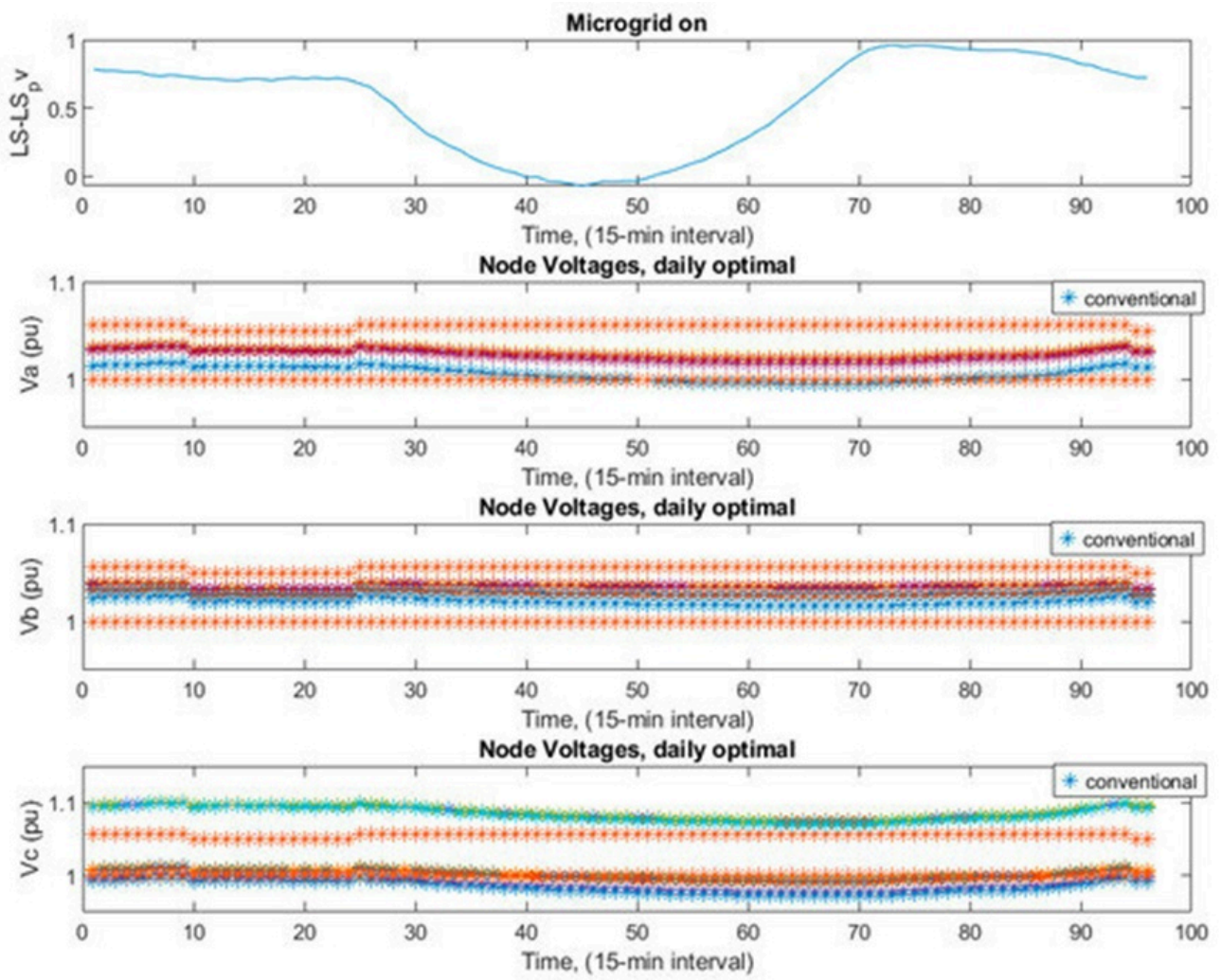


Figure 13. Daily node voltage variations in the base case: conventional local control with the microgrid connected.

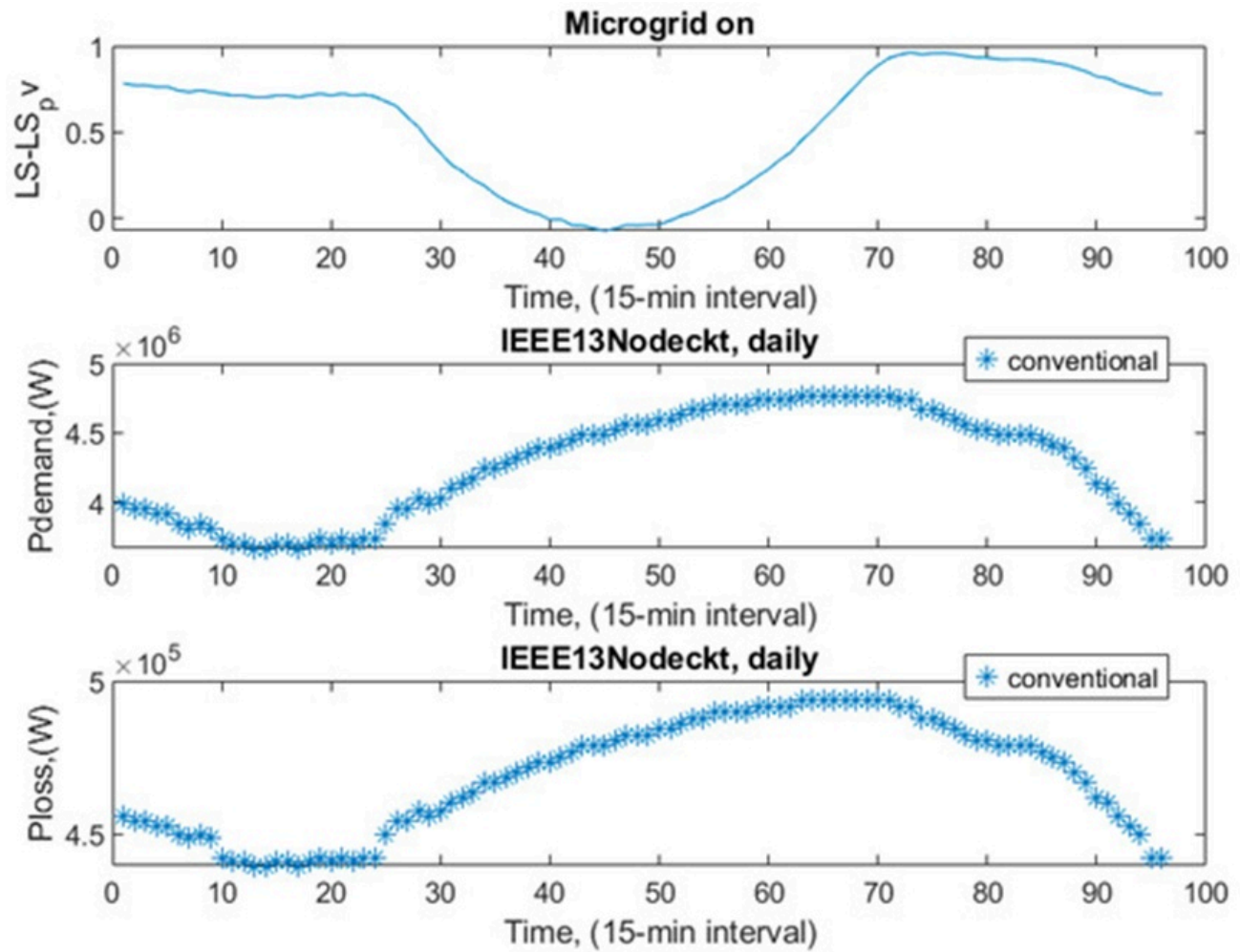


Figure 14. Daily changes in active power demand and losses under local control with the microgrid connected.

As evident in [Figure 14](#), even though the microgrid was connected and operational, the active power demand and losses did not align with the aggregated net load profile. This deviation stems directly from the local control strategy. The daily load shape of the main grid primarily dictated the active power demand and, consequently, the resulting active power losses.

The apparent, active, and reactive power profiles from the microgrid under local control are presented in [Figure 15](#). Apparent power remained essentially constant throughout the day, consistent with expectations under conventional local control. Active power followed the load profile, while reactive power moved in the opposite direction whenever active power decreased, thereby maintaining constant apparent power.

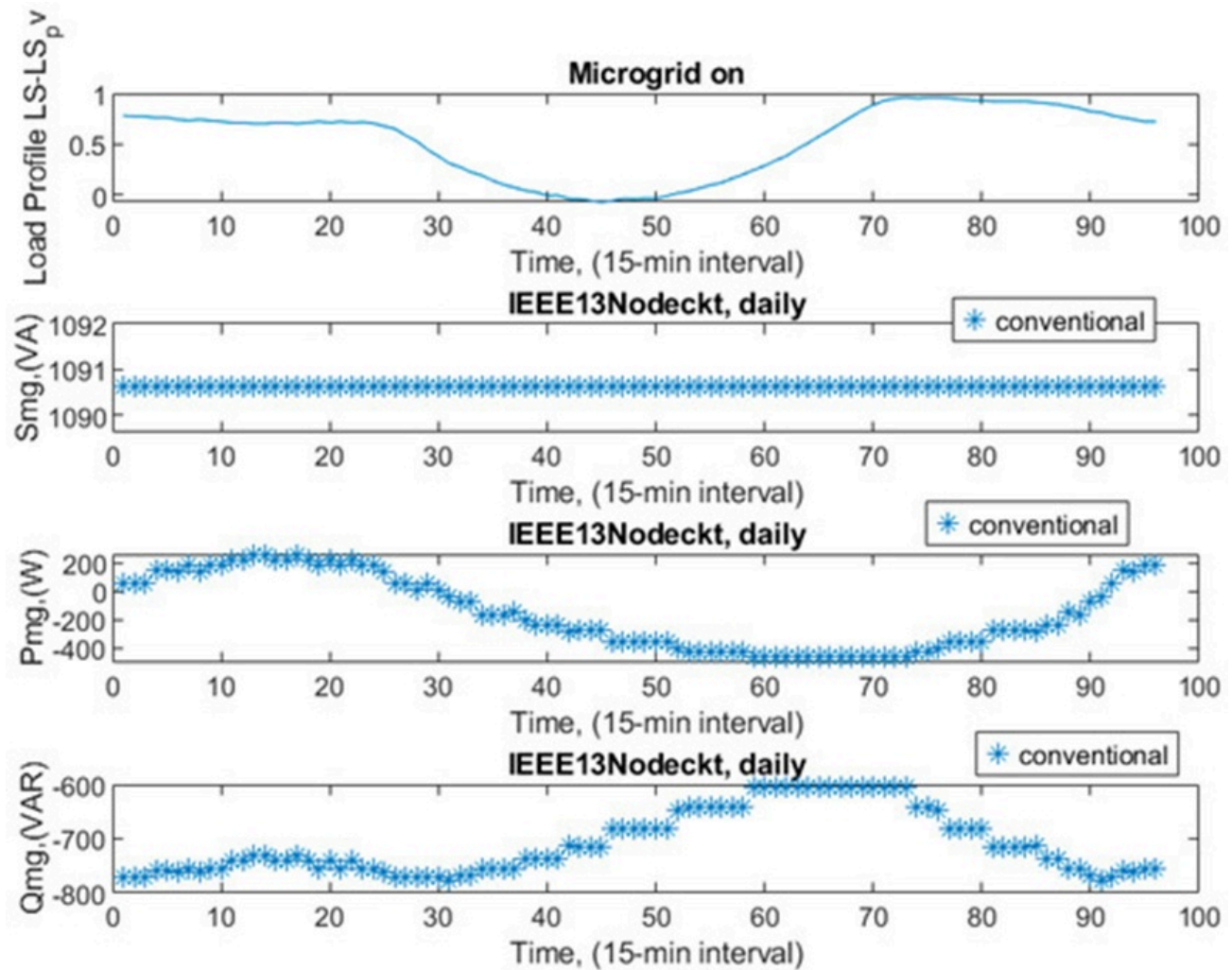


Figure 15. Apparent, active, and reactive power demand from the microgrid: daily pattern under local control.

Case 3: Microgrid is disconnected (off-grid). All control and coordination are implemented on the MATLAB platform using the coordinated control strategy

Load shapes for the main grid demand and PV generation were disabled in OpenDSS, and the control mode was set to off for regulators and capacitors. Management of the main grid load shape and coordination tasks was fully handled in MATLAB.

Tap positions are shown in [Figure 16](#), and node voltages in [Figure 17](#) are comparable to those in Case 1, with microgrid-related node voltages remaining nearly constant throughout the day. Overall, fluctuations were effectively minimized through coordinated control combined with the heuristic optimization algorithm.

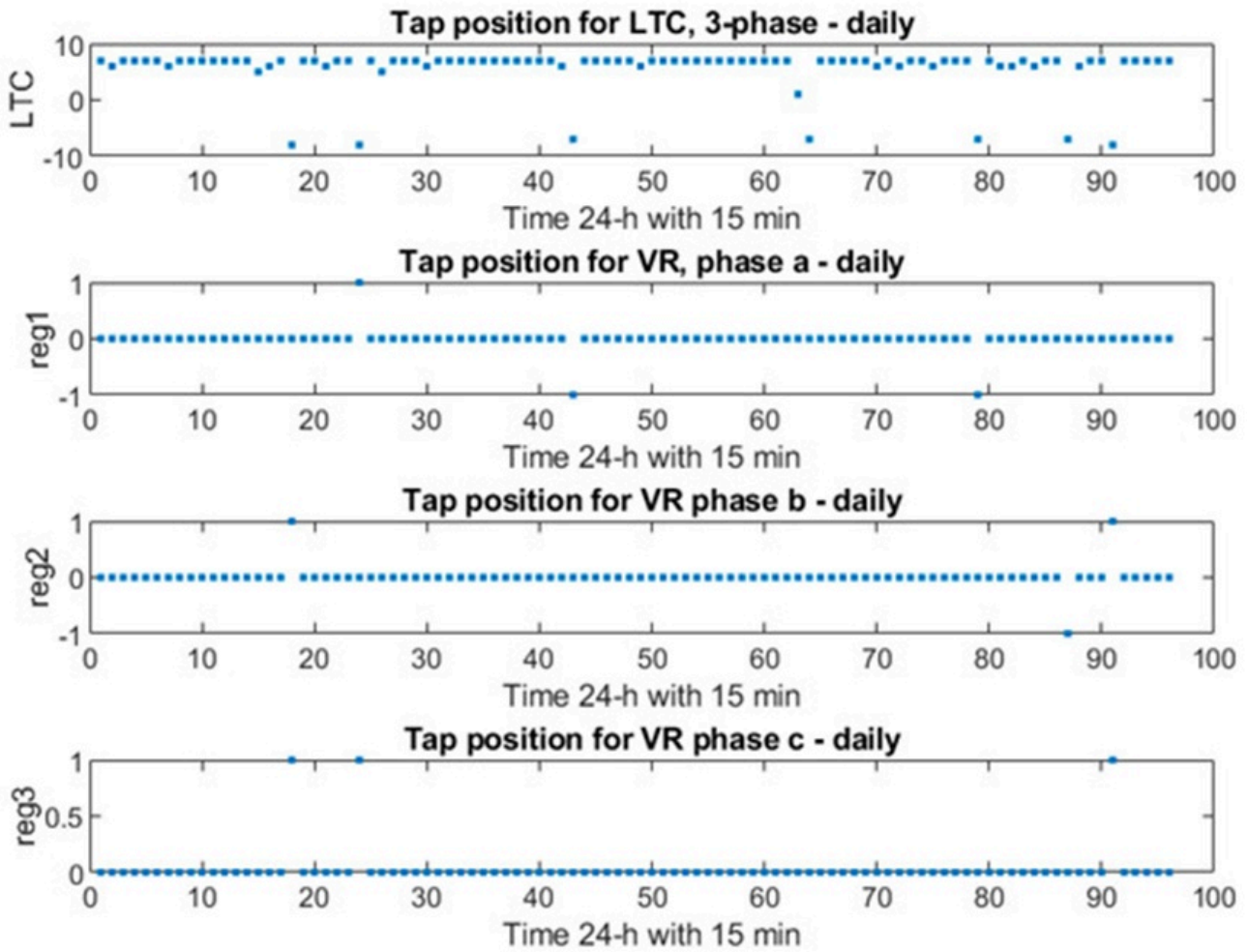


Figure 16. Tap positions of the LTC and VRs under coordinated control with the microgrid disconnected, daily optimal profile.

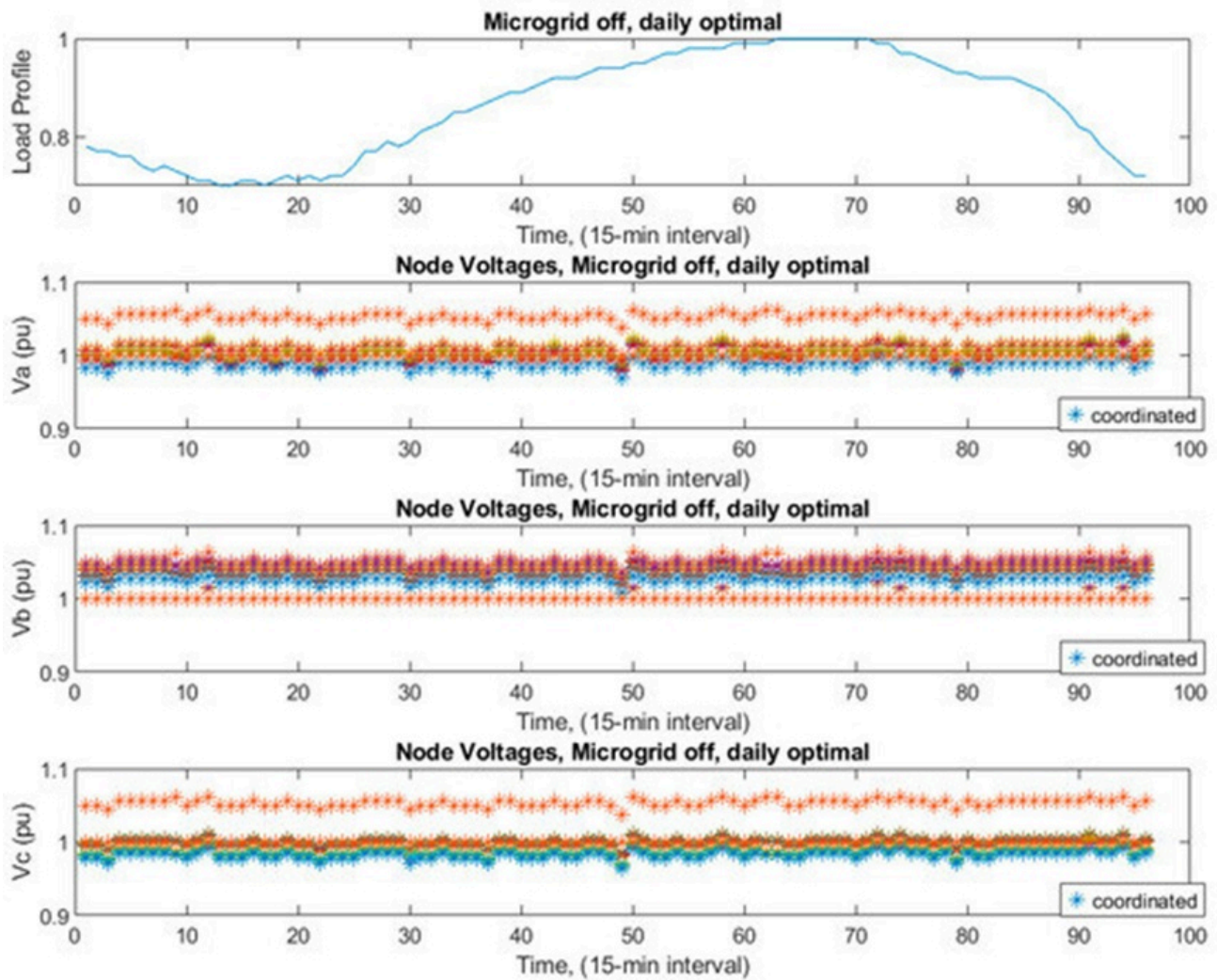


Figure 17. Daily node voltage variations under coordinated control with the microgrid disconnected.

Case 4: Microgrid is disconnected (off-grid) and operates under conventional local control without coordination—this serves as the base case

Only the main grid's daily load shape is active. As shown in [Figure 19](#), tap settings were elevated, similar to Case 2. The VR tap positions in Case 4 matched those in Case 2, as both relied on conventional local control—despite the microgrid being connected in Case 2 and disconnected in Case 4. Capacitor banks remained on (status 1) throughout the entire day. Due to the high tap settings, node voltages remained above 1 p.u., ranging from 1 to 1.1 p.u., as depicted in [Figure 20](#).

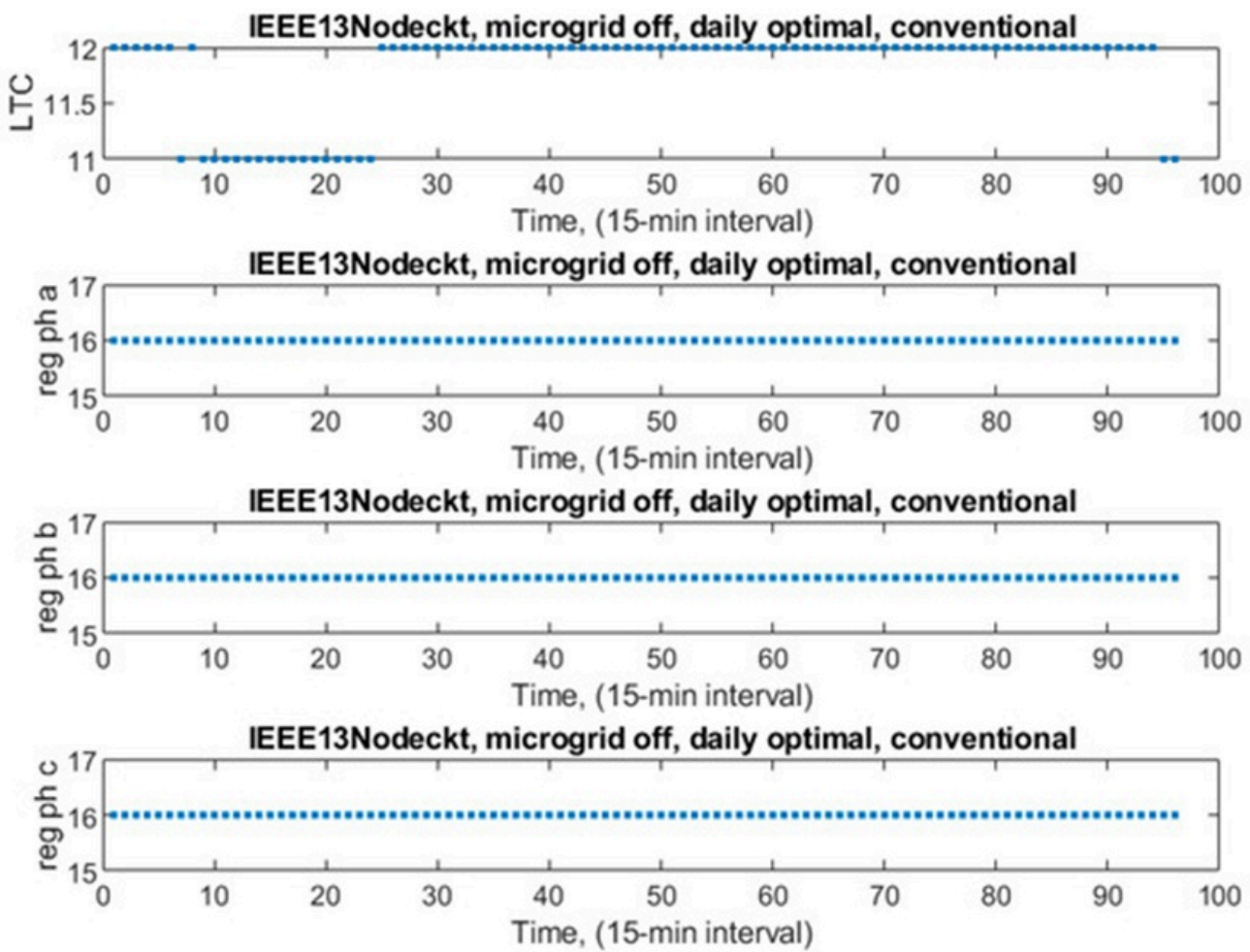


Figure 18. Tap positions of the LTC and VRs in the base case: conventional local control with the microgrid disconnected.

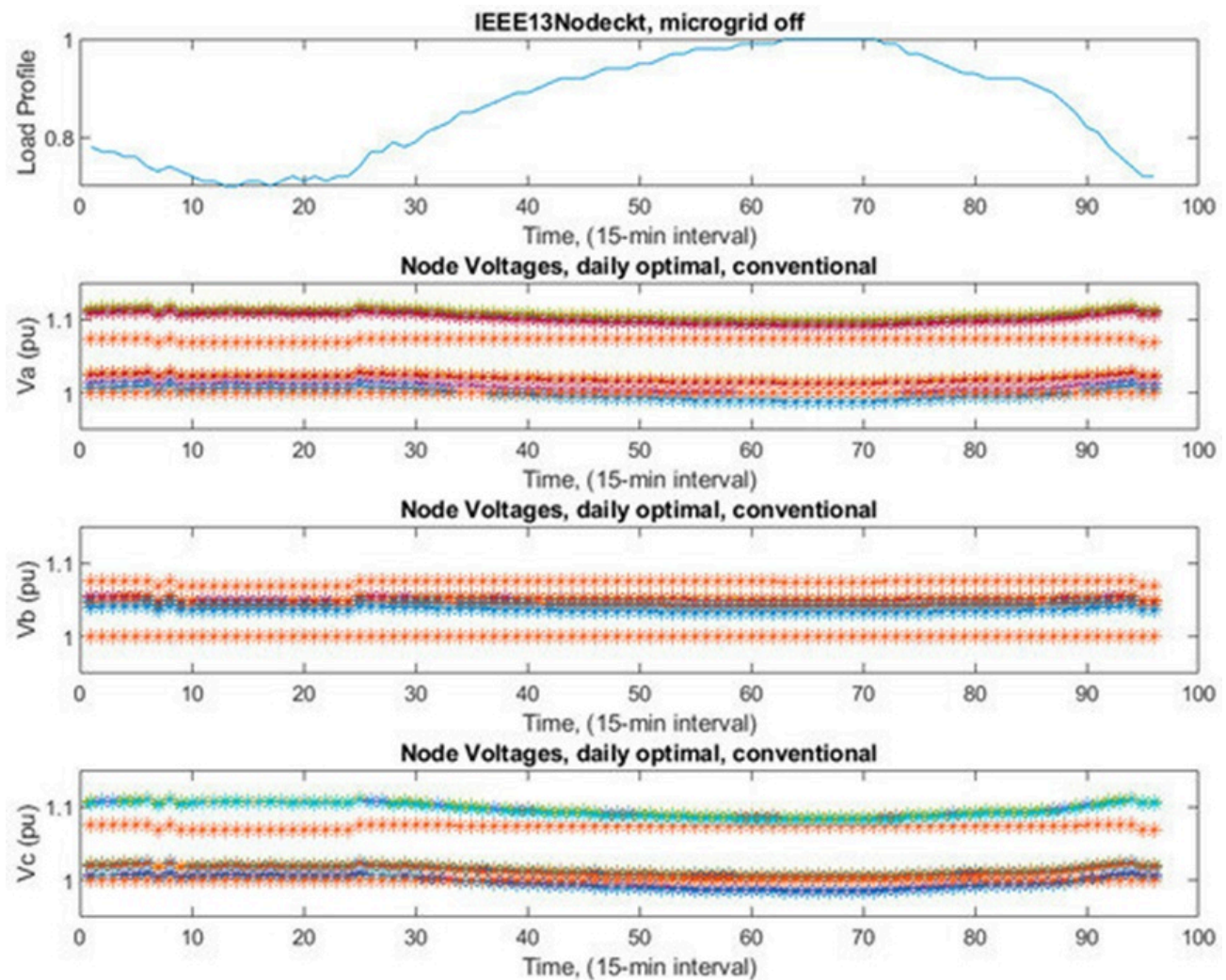


Figure 19. Daily node voltage variations in the base case: conventional local control with the microgrid disconnected.

Capacitor bank statuses remained at 1 throughout the day in the base case under conventional local control, with the microgrid disconnected.

Comparison of the Cases

Performance comparison between conventional local control and coordinated control during microgrid grid-connected operation:

Figure 20 displays side-by-side results for the baseline (conventional local control) versus the proposed coordinated control approach. According to both the **Figure 1** and **Table 1**, implementing coordination yielded an impressive 78.04% reduction in active power losses—a very substantial improvement. Active power demand was similarly lowered by 16.54%. Reactive power showed noticeable daily variation patterns under the coordinated scheme. Whenever solar irradiance was sufficient, the microgrid contributed surplus generation to help meet peak load periods.

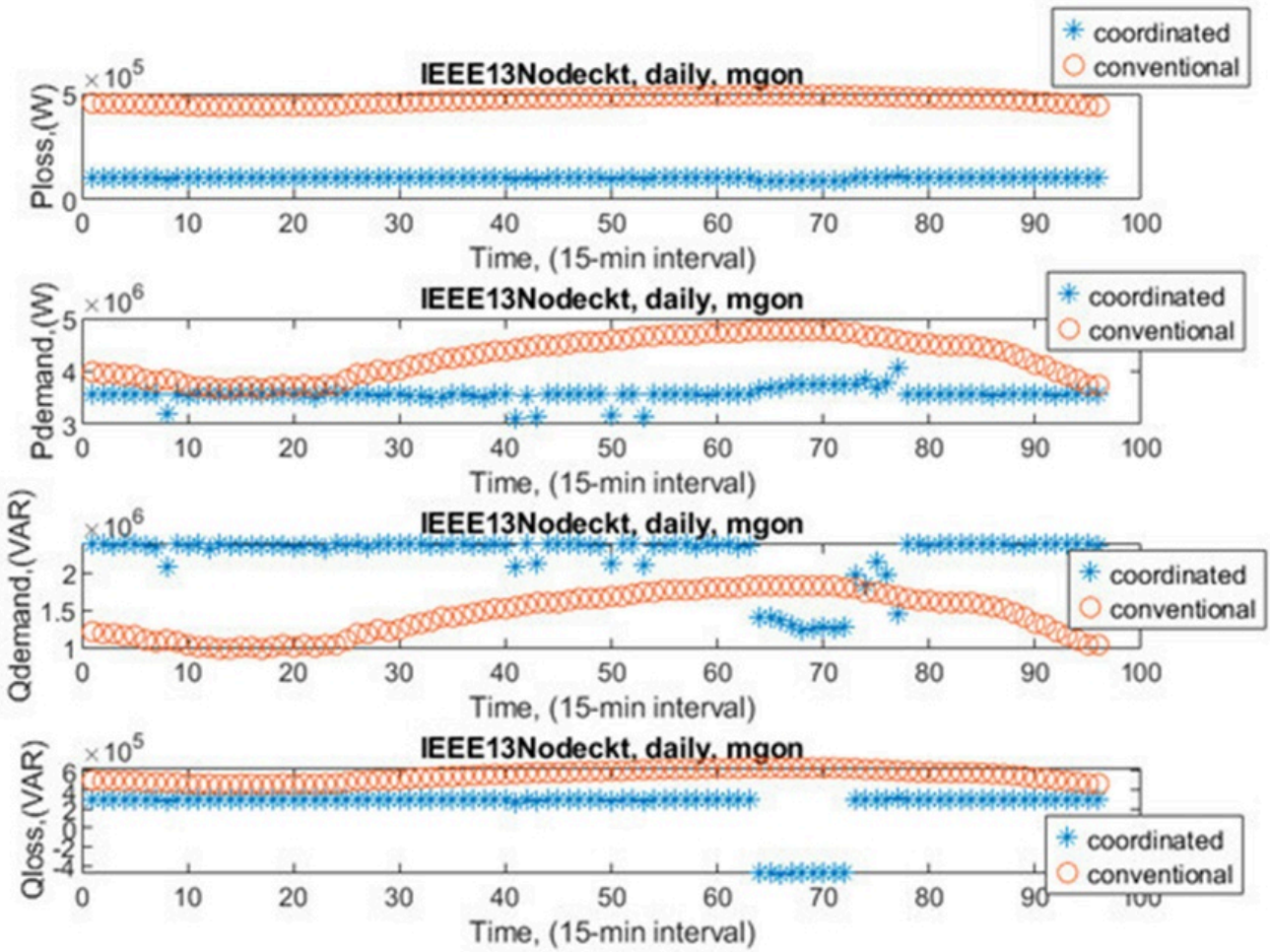


Figure 20. Daily variation curves of active power loss, active power demand, reactive power demand, and reactive power loss comparing conventional versus coordinated control strategies (microgrid connected).

Performance comparison between conventional local control and coordinated control during microgrid islanded/disconnected operation:

Figure 21 shows the corresponding comparison when the microgrid was not connected. As indicated by the Figure 2 and Table 2, coordinated operation reduced active power losses by 81.06%. Active power demand decreased by roughly 16.71%—a reduction almost identical to the grid-connected case reported in Table 1. Daily reactive power behavior also changed under coordination, although the pattern differed noticeably from the grid-connected scenario in Table 1. One of the most valuable outcomes was the much smoother, more uniform power consumption profile throughout the day. Peak active power was markedly mitigated, most likely thanks to better reactive power support and balancing achieved through the coordination strategy.

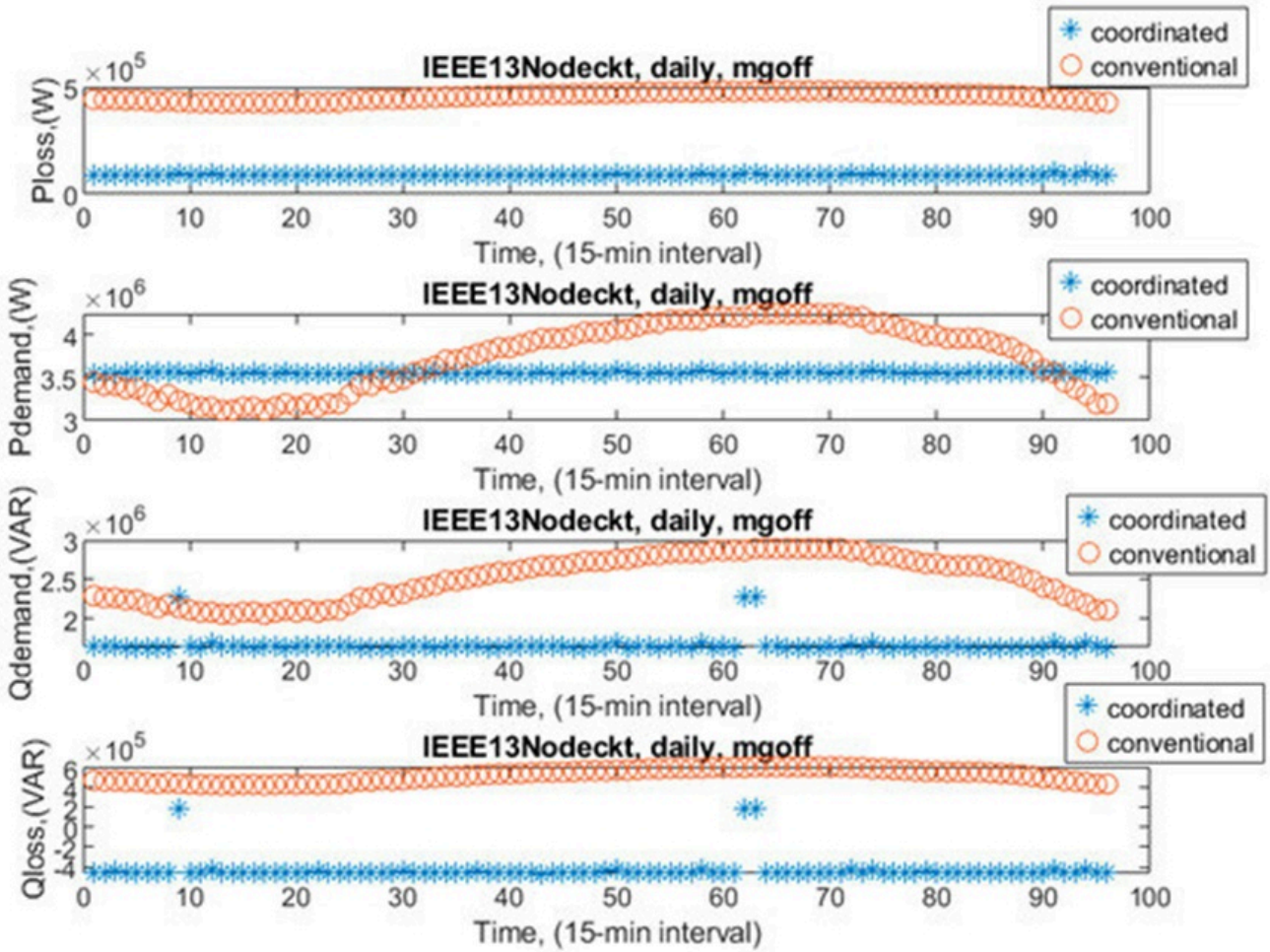


Figure 21. Daily variation curves of active power loss, active power demand, reactive power demand, and reactive power loss comparing conventional versus coordinated control strategies (microgrid disconnected).

Table 2. Microgrid grid-connected: coordinated control versus local control – Harmony Search (HS) algorithm outcomes.

Quantity	Conventional Control	Coordinated Control	Improvement (%)
Active Power Loss (Ploss)	45.0223×10^6 W	9.8877×10^6 W	78.04
Active Power Demand (Pdemand)	410.2777×10^6 W	342.4326×10^6 W	16.54
Reactive Power Demand (Qdemand)	138.1709×10^6 var	213.9738×10^6 var	−54.8617
Apparent Power Demand (Sdemand)	432.92×10^6 VA	403.79×10^6 VA	6.73

Overall comparison of all operating scenarios (Figure 22).

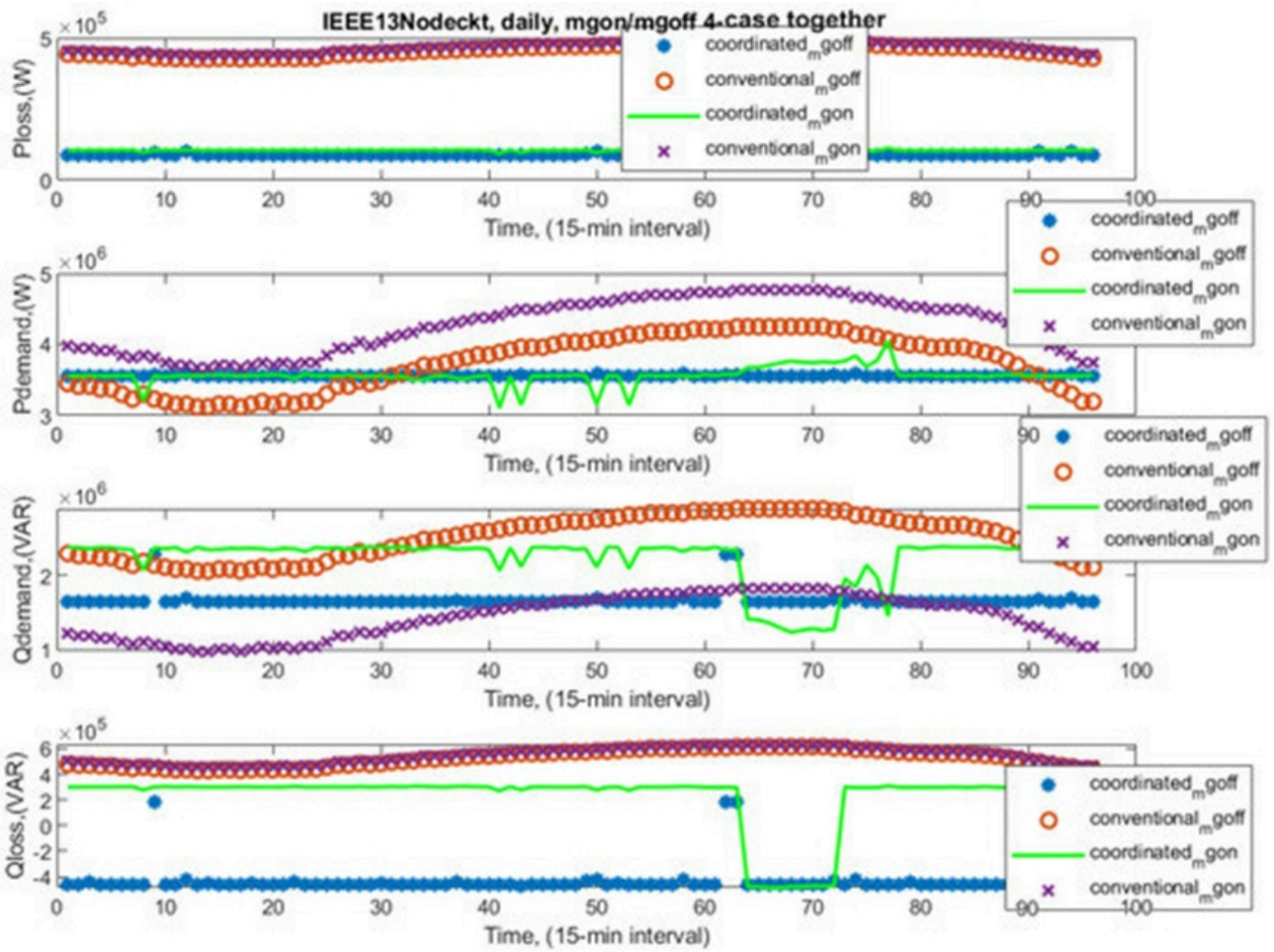


Figure 22. Summary view of the four studied cases: local control with microgrid connected/disconnected, and coordinated control with microgrid connected/disconnected.

Overall, the coordinated strategy consistently lowered P_{loss} , P_{demand} , and Q_{loss} across the evaluated scenarios, demonstrating clear benefits in power management efficiency. Even with occasional small oscillations observed during microgrid operation, the coordination approach still delivered very strong power management performance.

Table 2 details the specific percentage improvements achieved through coordination (with the microgrid connected) in active power loss, active power demand, reactive power demand, and main-grid apparent power. On a cumulative daily basis, coordination achieved a 78.04% decrease in active power loss and a 16.54% decrease in active power demand. Earlier published work combining coordination with Conservation Voltage Reduction (CVR) reported daily active power demand savings of 14%–17.19% [13]. Daily power loss reductions in those studies ranged from 75.79% to 84.43% [14], using a deterministic brute-force technique with deliberately limited search space to guarantee global optimality. The present study, by contrast, applied a heuristic (metaheuristic) optimization technique. Despite the stochastic nature of heuristic algorithms, the near-optimal solutions reported in **Table 3** were very close to the true global optima obtained deterministically (**Table 4**), without applying search-space reduction or the variable decoupling strategy used in the referenced work. When the microgrid was included, however, the heuristic results in **Table 1** showed about 1% lower active power demand savings and roughly 4% lower active power loss savings compared with the deterministic benchmark in **Table 4**.

Table 3. Microgrid islanded / off-grid: coordinated control versus local control – Harmony Search (HS) algorithm outcomes.

Parameter	Conventional control	Coordinated control	Improvement (%)
Active Power Loss (Ploss)	$45.0223 \times 10^6 \text{ W}$	$8.5265 \times 10^6 \text{ W}$	81.06
Active Power Demand (Pdemand)	$410.2777 \times 10^6 \text{ W}$	$341.7011 \times 10^6 \text{ W}$	16.71
Reactive Power Demand (Qdemand)	$138.1709 \times 10^6 \text{ var}$	$161.8527 \times 10^6 \text{ var}$	-17.14
Apparent Power Demand (Sdemand)	$432.9200 \times 10^6 \text{ VA}$	$378.1000 \times 10^6 \text{ VA}$	12.66

Table 4. No microgrid present: coordinated control versus local control – deterministic solution from prior work [13].

Parameter	Conventional control	Coordinated control	Improvement (%)
Active Power Loss (Ploss)	$40.316 \times 10^6 \text{ W}$	$7.1335 \times 10^6 \text{ W}$	82.31
Active Power Demand (Pdemand)	$346.253 \times 10^6 \text{ W}$	$292.391 \times 10^6 \text{ W}$	15.56

When examining apparent power drawn from the main grid, coordination with microgrid integration produced a 6.73% improvement, whereas coordination without microgrid support delivered a 12.66% daily reduction, almost twofold the benefit.

In this study, the Harmony Search (HS) optimization algorithm was employed to address the challenge of volt-var control and optimization. It enabled coordinated management of all relevant devices—such as load tap changers (LTCs), voltage regulators, and capacitor banks—and incorporated a PV-based microgrid into the distribution network. Simulations involved four distinct scenarios on a modified IEEE 13-node test feeder, where the microgrid was modeled as an IEEE 13-bus system with PV generation represented by three current sources. Outcomes across these cases were systematically compared.

In the first scenario, the microgrid operated in grid-connected mode under the proposed coordinated control strategy. The microgrid's local generation reduced current flow across the main grid circuit, leading to sharp decreases in both demand power and active power losses. Moreover, the stochastic nature of the heuristic algorithm effectively selected optimal setpoints for decision variables at each time step, successfully avoiding voltage fluctuations at the nodes.

The second scenario featured the microgrid in grid-connected mode, with no coordinated control. Devices related to volt-var were managed independently using traditional local control methods, with no overarching coordination. Capacitor banks remained permanently switched on, and voltage regulator tap positions were set excessively high. Consequently, node voltages exceeded 1 pu, reaching 1.1 pu.

In the third scenario, the microgrid was in islanded (off-grid) mode, but coordinated control was implemented. Coordination resulted in smaller voltage deviations between nodes than in the first case, consistent with expectations given the lack of PV-inverter reactive power support in islanded operation.

The fourth scenario served as the baseline: a microgrid disconnected and uncoordinated, with all devices under conventional local control. Results closely resembled those of the second scenario, with volt-var devices operating independently in accordance with standard local rules.

As illustrated in **Figures 9 and 17**—both depicting coordinated control cases in which voltages remained within acceptable limits—several sharp changes and oscillations occurred during daylight hours when the microgrid was grid-connected. These variations likely stemmed from uncertainties associated with PV generation.

Figures 13 and 19, which show conventional control outcomes, indicate that voltages remained within the upper portion of the allowable band. Although voltage profiles appeared generally smoother in these cases, slight drops in voltage levels were observed during periods of increased load following typical daily consumption patterns.

A direct comparison between local (conventional) control and coordinated control was performed for grid-connected microgrid operation. The results highlight that coordinated control delivers substantial advantages. In addition, the combination of microgrid integration and the coordination approach enabled smooth handling and fulfillment of peak demand periods.

Conclusion

This research utilized the Harmony Search (HS) algorithm—a metaheuristic optimization technique—to solve the volt-var control and optimization problem in a distribution system integrated with a PV-based microgrid. The primary goal was to minimize active power losses, flatten peak power demand profiles, and maintain node and phase voltages within specified limits, while coordinating all voltage- and reactive power-related devices to achieve optimal power management.

Through coordinated control, voltage fluctuations were effectively minimized across the day, ensuring greater stability within the target range. Furthermore, integration of the microgrid, combined with the coordination strategy, enabled efficient satisfaction and management of peak active power demands.

Tables 2 and 3 reveal a 3% difference in active power loss reduction between scenarios with and without microgrid integration, with the microgrid-disconnected case showing larger relative gains. For active power demand reductions, however, the improvements were virtually identical in both situations.

Tables 3 and 4 indicate that, in the absence of microgrid integration, the heuristic HS algorithm achieved performance improvements in active power loss and active power demand that were only about 1% lower than those of the previously examined deterministic method under both conventional and coordinated control. Considering computational demands, the HS approach offers a compelling balance: its simplicity provides a highly satisfactory tradeoff compared to more complex deterministic techniques.

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Conflict of interest

None

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Ethics statement

None

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