

Article

Rule-Based Real-Time Energy Management System for Curative Congestion Management in Low-Voltage Distribution Grids

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Abstract

The electrification of residential demand through electric vehicles (EVs), heat pumps (HPs), photovoltaic (PV) systems, and battery energy storage systems (BESSs) creates new congestion challenges in low-voltage (LV) grids. This study evaluates a transparent, deterministic, and real-time-capable rule-based energy management system (EMS) for curative thermal congestion management within a §14a EnWG-oriented setting. The EMS is implemented in MATLAB/Simulink and tested on a representative four-feeder LV network supplying 56 households. Congestion is detected from maximum phase root-mean-square currents using conservative transformer and feeder thresholds. After a threshold is reached, the EMS first activates available BESS support and then applies simultaneous feeder-wide EV limitation, batched round-robin curtailment, or staged feeder-wide reduction toward 4.2 kW. In the uncontrolled case, the Feeder 3 and transformer overload areas are 62.84 Ah and 48.50 Ah, respectively. All controlled scenarios remove at least 98.70% of the feeder overload and eliminate the transformer overload within the reported numerical precision. The batched strategy requires 328.54 Ah of cumulative feeder-current reduction, compared with 977.34 Ah for simultaneous control and 816.00 Ah for staged control, and achieves the highest feeder-relief efficiency. It therefore provides a balanced trade-off between congestion relief and intervention intensity for the investigated deterministic case.

Keywords: battery energy storage systems; congestion management; curative congestion management; distributed energy resources; electric vehicles; low-voltage distribution networks; real-time energy management; rule-based control



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1. Introduction

Low-voltage (LV) distribution grids are undergoing a major transformation due to the electrification of residential energy use and the rapid deployment of distributed energy resources. At the household level, electric vehicles (EVs), heat pumps (HPs), rooftop photovoltaic (PV) systems, and battery energy storage systems (BESSs) are increasingly installed at the same grid connection point. This development supports decarbonization and creates new flexibility potential, but it also changes the loading behavior of residential feeders and transformers. In particular, the simultaneous operation of high-power devices can create local congestion in LV networks. For this reason, congestion management at the household and feeder levels has become an important technical and regulatory issue.

The importance of this topic is reinforced by current deployment trends. According to the International Energy Agency (IEA), global electric car sales exceeded 17 million units in 2024, accounting for more than 20% of total global car sales [1]. In addition, heat

pumps already cover more than 10% of global heating demand in buildings [2]. These developments indicate that the electrification of transport and heating is no longer a future scenario, but an ongoing structural change. In residential areas, this change directly affects local grid operation because EV charging and HP operation often occur during concentrated time windows with high simultaneity. At the same time, PV generation and BESS operation introduce bidirectional power flows that may either support or stress the network depending on the applied control strategy.

In Germany, this technical challenge is closely linked to the regulatory framework of §14a of the Energy Industry Act (EnWG). As specified by the Bundesnetzagentur, the current implementation of §14a EnWG establishes a framework for integrating controllable consumer devices while preserving secure grid operation [3,4]. Since 1 January 2024, distribution system operators (DSOs) can no longer reject the connection of certain controllable devices solely because of expected congestion. Instead, such devices must be integrated in a way that allows temporary grid-oriented control during critical operating conditions [3]. In practical terms, this means that curative control strategies are becoming increasingly relevant for LV grid operation.

A substantial body of research has shown that coordinated operation of distributed resources can improve local grid conditions. Previous work has demonstrated that active prosumer participation and coordinated demand can improve the operating state of LV networks [5]. Residential PV systems combined with storage and controlled curtailment have also been shown to improve self-consumption and reduce peak power exchange with the grid [6]. More generally, home energy management systems are known to involve a trade-off between modeling complexity, uncertainty, and the coordination of heterogeneous devices [7]. Recent studies further confirm that increasing penetration of EVs, HPs, PV systems, and behind-the-meter storage creates growing congestion pressure in distribution grids and that flexibility-based mitigation can provide an alternative to pure grid reinforcement [8,9].

Optimization-based congestion-management methods and the rule-based approach considered in this work serve different operational objectives. Optimal power flow (OPF) determines network-wide control set points by solving a constrained optimization problem for a given system state, while model predictive control (MPC) repeatedly solves a finite-horizon optimization problem using a system model and predictions of future operating conditions. Stochastic scheduling additionally represents uncertainties in demand, generation, device availability, or electricity prices through scenarios or probability models. These methods are frequently applied to preventive or horizon-based coordination because they can anticipate expected congestion and schedule flexibility before a limit violation occurs. Nevertheless, OPF and MPC can also be implemented online when sufficiently accurate models, measurements, forecasts, communication infrastructure, and computational resources are available.

In contrast, the present work focuses specifically on curative real-time operation. The proposed EMS reacts directly when a measured transformer or feeder current reaches the corresponding congestion threshold and applies predefined BESS and EV control actions without solving an online optimization problem. A rule-based structure was therefore selected to provide deterministic execution, low computational complexity, transparent control decisions, and straightforward implementation in a real-time control environment. The objective of the present study is not to demonstrate global cost optimality or to claim superiority over OPF, MPC, or stochastic scheduling. Instead, it evaluates whether a simple and interpretable rule-based EMS can provide effective curative congestion relief under §14a EnWG. A quantitative benchmark against optimization-based approaches is outside the scope of the present study and is identified as an important direction for future work.

Learning-based methods provide an additional class of approaches for energy management. Supervised learning uses labeled historical data and can support tasks such as forecasting household demand, PV generation, device availability, or the occurrence of congestion. Unsupervised learning can identify operating patterns, clusters, and anomalies without requiring labeled target values. These approaches can provide useful information to an EMS; however, they do not by themselves define or guarantee feasible real-time control actions. Reinforcement learning (RL), and particularly deep reinforcement learning (DRL), directly learns a control policy through repeated interaction with an environment and can address nonlinear, uncertain, and high-dimensional EMS problems. Actor-critic algorithms, such as twin delayed deep deterministic policy gradient (TD3), are especially suitable for continuous control variables. At the vehicle level, Jia et al. proposed a TD3-based predictive EMS for a fuel-cell hybrid electric bus that incorporates future-speed and passenger-number predictions, demonstrating the potential of DRL to adapt energy allocation to complex and dynamic operating conditions [10]. DRL has also received increasing attention in home energy management systems for applications such as demand response, load scheduling, renewable energy integration, battery control, and EV charging [11].

The different EMS approaches involve important trade-offs. Supervised and unsupervised learning methods depend on the availability and representativeness of historical data and may be affected when actual operating conditions differ from the training data. RL and DRL offer greater adaptability and can learn complex control policies, but they require extensive training, careful reward-function and constraint design, and comprehensive safety and robustness validation before practical deployment. Their control decisions may also be less transparent than explicitly defined rules. In contrast, rule-based EMS approaches cannot generally guarantee an optimal solution and have limited adaptability to previously unseen operating conditions, but they provide deterministic actions, low online computational requirements, direct traceability, and straightforward verification against technical thresholds. These properties are particularly important for the present curative congestion-management application, in which the controller must react immediately and predictably to measured current-limit violations. Therefore, the rule-based method was selected as a transparent and operationally reliable approach for the scope of this study, while learning-based and hybrid rule-learning EMS architectures are identified as important directions for future research.

The preceding literature shows that rule-based EMS concepts and the individual intervention mechanisms considered in this study are already established. Accordingly, this work does not claim fundamental novelty for rule-based control as a general methodology, or for simultaneous, staged, and round-robin curtailment as isolated strategies. The research gap addressed here instead concerns their integration and controlled comparison within one transparent, measurement-triggered, and §14a-oriented framework for curative LV-grid congestion management. More specifically, the study addresses the following gaps:

- Limited implementation-oriented evidence is available on deterministic, solver-free household EMS control that reacts directly to measured feeder and transformer current-limit violations, rather than relying primarily on forecasts, preventive schedules, or repeated online optimization.
- Established curtailment-allocation mechanisms are often studied using different networks, assumptions, device populations, and performance indicators, which makes their operational trade-offs difficult to compare directly. A common benchmark under identical network, household, congestion-event, and BESS-support conditions is therefore needed.
- The trade-off between congestion relief and intervention intensity is not always quantified consistently. In particular, peak-current reduction should be considered together

with residual overload, overload duration or excess area, cumulative curtailment, and the number of households affected simultaneously.

- A clearer bridge is needed between an algorithmic comparison and a future real-time implementation, including deterministic execution, traceable decisions, fixed-step compatibility, and explicit recognition of the simplifying assumptions that limit direct DSO deployment.

Based on these gaps, the central research question is: To what extent can a transparent and real-time-capable rule-based EMS mitigate current-based feeder and transformer congestion, and how do different EV-curtailment allocation strategies trade off technical congestion relief against the intensity and breadth of intervention under a common §14a-oriented setting?

The main contributions of this work can be summarized as follows:

- A modular two-layer EMS architecture is formulated and implemented in MATLAB and Simulink R2024a. The supervisory layer detects current-based transformer and feeder congestion, while the household layer applies local BESS support and scenario-dependent EV control without requiring an online optimization solver.
- Three established curative EV control mechanisms—simultaneous feeder-wide limitation, batched round-robin curtailment, and staged feeder-wide reduction—are embedded in the same BESS-first control architecture and evaluated under identical network, household, and congestion conditions. The individual mechanisms are not claimed as new; the contribution is their harmonized implementation and direct comparison within one common framework.
- A quantitative comparison is provided using peak-current reduction, cumulative curtailed current, residual overload area, and the breadth of customer intervention. This reveals the trade-off between maximum technical relief and preservation of usable network and charging capacity, without making an unsupported quantitative fairness claim.
- The study provides an implementation-oriented interpretation of the results under §14a EnWG and explicitly identifies the limits of the current benchmark, including current-only congestion detection, simplified BESS dynamics, one dominant congested feeder, the absence of BESS-only and EV-only ablation cases, and the absence of formal fairness metrics.

The conceptual contribution of this paper is therefore not the invention of an isolated curtailment rule. It is the integrated and modular comparison framework that separates congestion detection, local storage support, and feeder-level EV intervention, thereby enabling established curative strategies to be evaluated consistently and transparently. The results show that all investigated strategies mitigate the studied overload, while the batched strategy achieves strong technical relief with substantially lower aggregate curtailment and fewer simultaneously affected households than the feeder-wide alternatives in the investigated case.

2. Materials and Methods

2.1. Studied Low-Voltage Network

The investigated system is a representative low-voltage (LV) distribution network derived from a SimBench LV case and adapted for the present study [12]. The network is supplied by one 20 kV/0.4 kV medium-voltage/low-voltage (MV/LV) transformer with a rated apparent power of 630 kVA. On the LV side, the transformer feeds four monitored radial feeders supplying a total of 56 residential households. The overall system structure and a representative household are shown in Figure 1. The investigated LV grid is operated

as a purely radial network without ring or meshed operation. This simplifying assumption allows feeder-local thermal congestion and the corresponding curative control actions to be evaluated without the additional power-flow interactions introduced by alternative switching configurations or closed-ring operation.

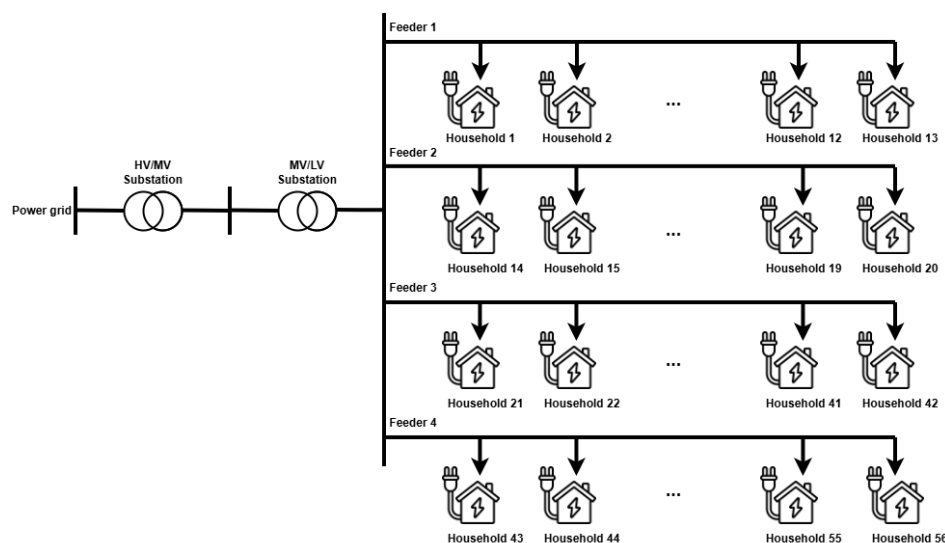


Figure 1. Studied LV distribution network with four radial feeders supplying 56 households, together with the modeled components of a representative household: electric vehicle (EV), photovoltaic (PV) system, battery energy storage system (BESS), heat pump (HP), and inflexible load.

All LV feeders are modeled using underground cables of type NAYY cable with four 240 mm² sector-shaped solid aluminum conductors and a rated voltage of 0.6 kV/1 kV. The corresponding per-kilometer parameters are the series resistance $r = 0.1267 \, \Omega/\text{km}$, the series reactance $x = 0.0798 \, \Omega/\text{km}$, and the shunt susceptance $b = 273.319 \, \mu\text{S}/\text{km}$. These parameters are used to represent cable losses and reactive effects in the feeder model. The thermal current limit of the cable is taken as $I_{\max} = 357 \, \text{A}$ and is used as the reference value for feeder congestion assessment [13,14].

2.2. Household Net-Power Formulation

The net power of household h at time step t is defined as follows:

$$P_{h,t}^{\text{net}} = P_{h,t}^{\text{inflex}} + P_{h,t}^{\text{EV}} + P_{h,t}^{\text{HP}} + P_{h,t}^{\text{BESS}} - P_{h,t}^{\text{PV}}, \quad (1)$$

The parameters in Equation (1) are defined as follows:

- h : household index.
- t : time step.
- $P_{h,t}^{\text{net}}$: net power of household h at time step t .
- $P_{h,t}^{\text{inflex}}$: non-controllable inflexible household-load power.
- $P_{h,t}^{\text{EV}}$: EV charging power.
- $P_{h,t}^{\text{HP}}$: heat-pump electrical power.
- $P_{h,t}^{\text{BESS}}$: BESS power, with positive values denoting charging and negative values denoting discharging.
- $P_{h,t}^{\text{PV}}$: PV generation power.

A positive value of $P_{h,t}^{\text{net}}$ indicates net power import from the grid.

2.3. Household Component Models

Each household is represented by separate models for inflexible load, PV generation, BESS operation, HP behavior, and EV charging. This modeling structure was chosen to capture the dynamic interaction between household assets and the supervisory energy management system (EMS).

Household heterogeneity is represented through individual inflexible-load profiles and household-specific EV characteristics, including arrival and departure times, battery capacities, and model parameters. Consequently, EV availability and charging demand vary across the 56 households. For simplification, all households use the same time-dependent PV production profile and the common HP parameter set reported in Table 1. These common inputs represent shared local irradiance and a uniform building archetype, while the heterogeneous load and EV data create distinct household net-power trajectories.

Table 1. Heat-pump parameter set used in all households.

Parameter	Value	Unit	Parameter	Value	Unit
R	0.004	K/W	C	8,000,000	J/K
T_{set}	21	°C	COP_0	3	–
k_{COP}	0.05	1/°C	COP_{min}	1.5	–
COP_{max}	5	–	Q_0	7000	W
a_Q	15	W/°C	Q_{min}	3000	W
Q_{hi}	9000	W	$P_{\text{el,max}}$	6000	W
db	0.3	°C	K_q	8000	W/°C
τ	60	s			

2.3.1. Inflexible Load Model

The inflexible load represents ordinary household demand that is not directly controlled by the EMS. It is implemented as a predefined time-varying profile and forms the non-flexible part of household consumption. In the overall household model, this component defines the basic loading level on top of which EV charging, HP operation, PV generation, and BESS operation are superimposed. A representative Day 2 profile is shown in Figure 2a.

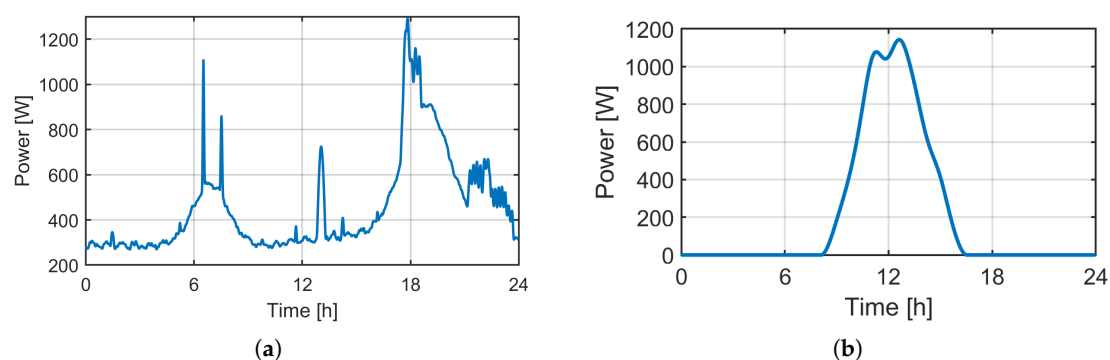


Figure 2. Representative Day 2 household input profiles used in the EMS framework: (a) Inflexible household load and (b) PV generation profile.

2.3.2. Photovoltaic Model

The PV system is modeled as a household-level distributed generation source. Its output follows a time-varying generation profile and is treated as a predefined local generation signal. From the feeder perspective, PV generation reduces household net demand and can partially compensate for the loading caused by EV charging, HP operation, or the inflexible load. A representative Day 2 PV profile is shown in Figure 2b.

2.3.3. Battery Energy Storage System Model

The BESS is modeled as a bidirectional unit that can absorb power during charging and inject power during discharging. Its operation is constrained by power limits, state-of-charge (SOC) limits, charge/discharge efficiency, and energy capacity. In the present study, the BESS serves three main purposes: increasing local PV self-consumption, reducing household peak demand, and acting as the first curative countermeasure during congestion events. A constant BESS efficiency of $\eta_{\text{BESS}} = 0.9$ is assumed.

The BESS representation is intentionally simplified to support the grid-level evaluation of the proposed curative EMS. The model includes fixed charging and discharging power limits, state-of-charge limits, energy capacity, and a constant charge/discharge efficiency. However, it does not include battery degradation and degradation costs, inverter apparent-power and reactive-power constraints, ramp-rate limits, thermal limitations, state-of-charge-dependent power capability, or power- and state-dependent efficiency. In the supervisory control logic, the BESS is assumed to deliver the commanded active power whenever the predefined state-of-charge and power limits are satisfied. This assumption reduces the model complexity and allows the study to isolate the short-term curative congestion-management behavior.

Consequently, the simulated BESS contribution should be interpreted as an idealized estimate of the immediately available storage flexibility and may overestimate the congestion relief achievable in practical installations. A deployment-oriented implementation would require a lower-level BESS and inverter controller that enforces inverter capability, ramp-rate, thermal, and state-dependent operating constraints. It should also account for battery degradation when determining the technically and economically feasible dispatch. Incorporating these effects and evaluating their influence on the BESS-first strategy are considered important directions for future work.

The discrete-time BESS SOC update is defined as follows:

$$\text{SOC}_h^{\text{BESS}}[k+1] = \text{sat} \left(\text{SOC}_h^{\text{BESS}}[k] + \frac{T_s}{E_{\text{cap}}^{\text{BESS}} \cdot 3600} \begin{cases} \eta_{\text{BESS}} P_h^{\text{BESS}}[k], & P_h^{\text{BESS}}[k] \geq 0, \\ \frac{P_h^{\text{BESS}}[k]}{\eta_{\text{BESS}}}, & P_h^{\text{BESS}}[k] < 0, \end{cases} \right), \quad (2)$$

The parameters in Equation (2) are defined as follows:

- $\text{SOC}_h^{\text{BESS}}[k]$: state of charge of the BESS in household h at time step k .
- h : household index.
- k : discrete simulation time-step index.
- T_s : simulation sample time in seconds.
- $P_h^{\text{BESS}}[k]$: BESS power at time step k ; positive values denote charging and negative values denote discharging.
- η_{BESS} : constant BESS charge/discharge efficiency, set to 0.9 in this study.
- $E_{\text{cap}}^{\text{BESS}}$: BESS energy capacity in watt-hours.
- $\text{sat}(\cdot)$: saturation function that enforces the admissible BESS SOC range.

2.3.4. Heat-Pump Model

The HP is modeled as a control-oriented gray-box component that converts electrical power into delivered heat using a temperature-dependent coefficient of performance (COP), a simple comfort controller, power limits, and first-order thermal dynamics. In the present study, the HP is represented and monitored in all households, but it is not directly curtailed by the congestion-management logic.

The indoor-temperature dynamics are described by the first-order thermal model:

$$C \frac{dT_{\text{in}}(t)}{dt} = \frac{T_{\text{out}}(t) - T_{\text{in}}(t)}{R} + Q_{\text{th}}(t), \quad (3)$$

The parameters in Equation (3) are defined as follows:

- $T_{\text{out}}(t)$: outdoor temperature at time t .
- $T_{\text{in}}(t)$: indoor temperature at time t .
- $Q_{\text{th}}(t)$: thermal power delivered by the heat pump.
- R : equivalent building thermal resistance.
- C : equivalent building thermal capacitance.

The COP is approximated by

$$\text{COP}(t) = \text{sat}(\text{COP}_0 + k_{\text{COP}}T_{\text{out}}(t), \text{COP}_{\text{min}}, \text{COP}_{\text{max}}), \quad (4)$$

The parameters in Equation (4) are defined as follows:

- $\text{COP}(t)$: coefficient of performance of the heat pump at time t .
- COP_0 : nominal offset of the COP model.
- k_{COP} : coefficient describing the dependence of COP on outdoor temperature.
- COP_{min} : minimum admissible COP.
- COP_{max} : maximum admissible COP.
- $\text{sat}(\cdot)$: saturation function that constrains the COP to its feasible operating range.

The thermal controller computes the temperature error,

$$e(t) = T_{\text{set}} - T_{\text{in}}(t), \quad (5)$$

and the resulting heat demand,

$$Q_{\text{demand}}(t) = \begin{cases} 0, & e(t) \leq db, \\ \text{sat}(K_q(e(t) - db), 0, Q_{\text{hi}}), & e(t) > db, \end{cases} \quad (6)$$

The parameters in Equations (5) and (6) are defined as follows:

- $e(t)$: indoor-temperature control error.
- T_{set} : indoor-temperature setpoint.
- db : controller deadband.
- K_q : proportional gain used to calculate the thermal demand.
- $Q_{\text{demand}}(t)$: calculated thermal-power demand.
- Q_{hi} : upper thermal-demand limit.

The maximum available thermal output is defined as

$$Q_{\text{max}}(t) = \text{sat}(Q_0 + a_Q T_{\text{out}}(t), Q_{\text{min}}, Q_{\text{hi}}), \quad (7)$$

The parameters in Equation (7) are defined as follows:

- $Q_{\text{max}}(t)$: maximum available thermal output at time t .
- Q_0 : nominal offset of the maximum-thermal-output model.
- a_Q : coefficient describing the dependence of available thermal output on outdoor temperature.
- Q_{min} : minimum thermal-output limit.
- Q_{hi} : upper thermal-output limit.

The commanded and feasible thermal outputs are given by Equations (8) and (9), respectively.

$$Q_{\text{cmd}}(t) = \min(Q_{\text{demand}}(t), Q_{\text{max}}(t)), \quad (8)$$

$$Q_{\text{ref}}(t) = \min(Q_{\text{cmd}}(t), \text{COP}(t) P_{\text{el,max}}), \quad (9)$$

The parameters in Equations (8) and (9) are defined as follows:

- $Q_{\text{cmd}}(t)$: commanded thermal output after applying the heat-demand and availability limits.
- $Q_{\text{ref}}(t)$: feasible thermal-output reference.
- $P_{\text{el,max}}$: maximum heat-pump electrical power.

To represent non-instantaneous heat delivery, the thermal output follows the reference through a first-order lag:

$$\tau \frac{dQ_{\text{th}}(t)}{dt} + Q_{\text{th}}(t) = Q_{\text{ref}}(t), \quad (10)$$

The parameters in Equation (10) are defined as follows:

- τ : heat-pump first-order time constant.
- $Q_{\text{th}}(t)$: actual delivered thermal power.
- $Q_{\text{ref}}(t)$: feasible thermal-output reference.

The electrical power is then computed as shown in Equation (11):

$$P_{\text{el,HP}}(t) = \frac{Q_{\text{th}}(t)}{\text{COP}(t)}, \quad (11)$$

The parameters in Equation (11) are defined as follows:

- $P_{\text{el,HP}}(t)$: heat-pump electrical power at time t .
- $Q_{\text{th}}(t)$: delivered thermal power.
- $\text{COP}(t)$: heat-pump coefficient of performance.

The electrical power is limited to the interval $[0, P_{\text{el,max}}]$. The parameter set used for the HP model is listed in Table 1.

2.3.5. Electric Vehicle Model

The EV is modeled as a controllable household load whose charging power can be set by the EMS and curtailed during congestion events. The model includes a vehicle availability window, a maximum charging power, an SOC update, and a congestion-mode limitation path [15,16].

The EV connection status is defined by

$$c_t = \begin{cases} 1, & t_{\text{arr}} \leq t \leq t_{\text{dep}}, \\ 0, & \text{otherwise,} \end{cases} \quad (12)$$

The parameters in Equation (12) are defined as follows:

- c_t : EV connection-status variable, equal to 1 when the vehicle is connected and 0 otherwise.
- t : current time.
- t_{arr} : EV arrival time.
- t_{dep} : EV departure time.

Charging is enabled only if the EV is connected and the SOC is below the upper SOC limit,

$$u_t = c_t \cdot \mathbf{1}\{\text{SOC}_{\text{EV},t} < \text{SOC}_{\text{max}}\}, \quad (13)$$

and the commanded charging power is

$$P_{\text{cmd},t} = u_t \cdot \min(p_{\text{request},t}, P_{\text{max}}), \quad (14)$$

The parameters in Equations (13) and (14) are defined as follows:

- u_t : EV charging-enable variable.
- $1\{\cdot\}$: indicator function, equal to 1 when its condition is true and 0 otherwise.
- $\text{SOC}_{\text{EV},t}$: EV battery state of charge at time t .
- SOC_{max} : upper EV state-of-charge limit.
- $P_{\text{cmd},t}$: EV charging-power command before congestion-related limitation.
- $p_{\text{request},t}$: requested EV charging power.
- P_{max} : maximum EV charging power.

To represent the §14a-style limitation, the EV model uses a supervisory mode signal with $\text{mode} = 0$ for normal operation and $\text{mode} = 1$ for congestion mode. For Scenario 2 and the selected batches in Scenario 3, and as the final lower setpoint in Scenario 4, the EV charging-power limit is defined as

$$P_{14a} = 4.2 \text{ kW}, \quad (15)$$

Let $P_{\text{lim},t}^{(s)}$ denote the scenario-dependent charging-power limit assigned to the EV under consideration. In Scenario 2, it is set directly to P_{14a} for all controllable EVs on the affected feeder. In Scenario 3, it is set to P_{14a} only for EVs in the active household batch. In Scenario 4, it follows the active intermediate stage and reaches P_{14a} at the final stage. The actual EV charging power is then given by

$$P_{\text{EV},t}^{(s)} = \begin{cases} \min(P_{\text{cmd},t}, P_{\text{lim},t}^{(s)}), & \text{mode}_t = 1, \\ P_{\text{cmd},t}, & \text{mode}_t = 0. \end{cases} \quad (16)$$

The parameters in Equations (15) and (16) are defined as follows:

- P_{14a} : final EV charging-power limit used in the investigated curative strategies, set to 4.2 kW.
- s : control-scenario index.
- $P_{\text{lim},t}^{(s)}$: scenario-dependent EV charging-power limit assigned at time t .
- $P_{\text{EV},t}^{(s)}$: EV charging power applied in scenario s .
- $P_{\text{cmd},t}$: EV charging-power command before curtailment.
- mode_t : supervisory mode signal, with $\text{mode}_t = 0$ for normal operation and $\text{mode}_t = 1$ for congestion mode.

The EV battery SOC is represented in this study using a simplified discrete-time energy-balance model. In practical lithium-ion battery systems, battery performance and SOC evolution are also influenced by the applied current rate and thermal operating conditions. Divakaran et al. investigated the electro-thermal behavior of a reusable lithium-ion battery module over complete discharge cycles at different C-rates and included SOC in the battery heat-generation formulation, thereby illustrating the coupling between SOC, current, and temperature [17]. These electro-thermal effects are not explicitly included in the present EV model because the focus of this study is the grid-level behavior of the curative EMS. Their inclusion in a more detailed electro-thermal EV battery model is identified as future work.

The discrete-time EV SOC update is given by

$$\text{SOC}_{\text{EV}}[k+1] = \text{sat}\left(\text{SOC}_{\text{EV}}[k] + \frac{T_s \eta_{\text{ch}} P_{\text{EV}}^{(s)}[k]}{E_{\text{cap}} \cdot 3600}\right), \quad (17)$$

The parameters in Equation (17) are defined as follows:

- $\text{SOC}_{\text{EV}}[k]$: EV battery state of charge at time step k .
- T_s : simulation sample time in seconds.
- η_{ch} : EV charging efficiency, assumed constant at 0.8.
- $P_{\text{EV}}^{(s)}[k]$: EV charging power applied in scenario s at time step k .
- E_{cap} : EV battery energy capacity in watt-hours.
- $\text{sat}(\cdot)$: saturation function that enforces the admissible EV SOC range.

2.4. Congestion Detection and Rule-Based EMS

In the present study, congestion is intentionally formulated as a current-based thermal constraint at the LV transformer and the monitored feeders. Although the MATLAB/Simulink network model provides access to voltage magnitudes, phase currents, and other electrical measurements, only the transformer and feeder current magnitudes are used as input variables for congestion detection and curative control. Consequently, voltage-magnitude limits, voltage unbalance, reactive-power constraints, and combined thermal-voltage security criteria are not included in the present EMS decision logic. This simplifying assumption was adopted to isolate the main research question of this work, namely, the evaluation of a transparent and real-time-capable rule-based EMS for curative thermal congestion management under §14a EnWG. Therefore, the present results are primarily applicable to current-dominated congestion conditions. Extending the EMS to include voltage, unbalance, reactive-power, and combined operational constraints is considered an important direction for future work.

The EMS continuously monitors the transformer LV-side current magnitude $I_{\text{tr},t}$ and the feeder current magnitude $I_{f,i,t}$ for each feeder i . In three-phase operation, the monitored quantity is taken as the maximum phase RMS current, $I_{\text{tr},t} = \max(I_{\text{tr},a,t}, I_{\text{tr},b,t}, I_{\text{tr},c,t})$, and $I_{f,i,t} = \max(I_{f,i,a,t}, I_{f,i,b,t}, I_{f,i,c,t})$.

For the transformer with rated apparent power $S_r = 630 \text{ kVA}$ and LV line-to-line voltage $U_{\text{LV}} = 0.4 \text{ kV}$, the rated current is $I_{\text{tr,max}} = \frac{S_r}{\sqrt{3} U_{\text{LV}}} \approx 909 \text{ A}$, and the corresponding transformer congestion threshold is defined as $I_{\text{tr,th}} = 0.9 I_{\text{tr,max}} \approx 818 \text{ A}$.

For the feeder cable, the admissible current is $I_{f,\text{max}} = 357 \text{ A}$, and the feeder congestion threshold is $I_{f,\text{th}} = 0.9 I_{f,\text{max}} \approx 321 \text{ A}$.

The 10% security margin provides a conservative operating buffer below the equipment ratings [18]. It is a fixed design assumption in the present controller and is not derived from a probabilistic uncertainty analysis.

The transformer congestion flag, feeder congestion flag, and global congestion signal are defined as $o_{\text{tr},t} = \mathbf{1}\{I_{\text{tr},t} \geq I_{\text{tr,th}}\}$, $o_{f,i,t} = \mathbf{1}\{I_{f,i,t} \geq I_{f,\text{th}}\}$, and $o_t = \max(o_{\text{tr},t}, \max_i o_{f,i,t})$.

The present study evaluates one dominant congested feeder and assumes a radial LV topology without ring operation. Therefore, simultaneous congestion across multiple feeders and network-wide interactions under meshed or alternative switching configurations are not explicitly simulated. In the considered radial structure, each feeder forms a separate downstream branch, so a load reduction on one feeder primarily affects the current of that feeder. Nevertheless, the feeders are not completely independent because they remain coupled through the shared transformer and the common LV bus.

A multi-feeder extension of the proposed EMS would therefore apply feeder-local congestion-management actions independently and in parallel on each affected radial feeder, while a transformer-level supervisory controller would coordinate the combined actions and continuously monitor the shared transformer loading. Such coordination would be required when several feeders are congested simultaneously, when the transformer limit is also violated, or when multiple feeder controllers request limited flexibility resources. The implementation and validation of multi-feeder coordination, ring operation,

and network-wide interactions are outside the scope of the present study and are identified as future work.

The EMS uses a two-layer rule-based architecture. The supervisory layer monitors transformer and feeder currents and switches between normal and congestion modes, while the household layer applies local BESS and PV operating rules and dispatches EV curtailment actions. HP behavior is modeled and monitored but not directly curtailed.

The supervisory logic is illustrated in Table 2. In normal mode, the EMS prioritizes local PV utilization under a no-export assumption. PV surplus first charges the BESS if the SOC allows it, and any remaining surplus is curtailed. During PV deficit, the BESS discharges first and the remaining deficit is imported from the grid, as shown in Table 3.

Table 2. Congestion detection algorithm.

Input: $I_{tr,th}$, $I_{f,th}$, measured currents $I_{tr,k}$ and $I_{f,k}$ for all feeders $f \in \mathcal{F}$.
Output: System state S_k .

1. Read current measurements.
2. Measure transformer current $I_{tr,k}$.
3. Measure feeder current $I_{f,k}$ for each feeder $f \in \mathcal{F}$.
4. If $(I_{tr,k} \geq I_{tr,th})$ or $(\exists f \in \mathcal{F} : I_{f,k} \geq I_{f,th})$, then:
 - 4.1 $S_k \leftarrow \text{Congestion}$.
5. Else:
 - 5.1 $S_k \leftarrow \text{Normal}$.
6. Return S_k .

Table 3. Rule-based battery scheduling algorithm under normal network operation.

Input: $P_{load}[k]$, $P_{PV}[k]$, $SOC_{batt}[k]$, SOC_{min} , SOC_{max} , P_{ch}^{max} , P_{dis}^{max} .
Output: Battery power $P_{batt}[k]$, grid power $P_{grid}[k]$, curtailed PV power $P_{curt}[k]$.

1. Compute the net power balance:
 $P_{net}[k] \leftarrow P_{load}[k] - P_{PV}[k]$.
2. Initialize:
 $P_{batt}[k] \leftarrow 0$, $P_{grid}[k] \leftarrow 0$, $P_{curt}[k] \leftarrow 0$.
3. If $P_{net}[k] \leq 0$, then:
 - 3.1 $P_{sur}[k] \leftarrow -P_{net}[k]$.
 - 3.2 If $SOC_{batt}[k] < SOC_{max}$, then:
 - 3.2.1 Charge the battery with available surplus power, limited by P_{ch}^{max} .
 - 3.2.2 Curtail the remaining surplus PV power, if any.
 - 3.3 Else:
 - 3.3.1 Keep the battery idle.
 - 3.3.2 Curtail the surplus PV power.
4. Else, if $P_{net}[k] > 0$, then:
 - 4.1 $P_{def}[k] \leftarrow P_{net}[k]$.
 - 4.2 If $SOC_{batt}[k] > SOC_{min}$, then:
 - 4.2.1 Discharge the battery to supply the deficit, limited by P_{dis}^{max} .
 - 4.2.2 Supply the remaining deficit from the grid.
 - 4.3 Else:
 - 4.3.1 Keep the battery idle.
 - 4.3.2 Supply the full deficit from the grid.
5. Return $P_{batt}[k]$, $P_{grid}[k]$, and $P_{curt}[k]$.

The BESS-first and EV-curtailment-second ordering is a deliberate rule-based design choice rather than the result of an optimization procedure or a proof of global optimality. At the household level, an EMS can, in principle, apply household-specific preferences and different priorities among flexible devices. For example, individual households could

prioritize EV charging, battery availability, self-consumption, or other user-defined objectives. However, considering a different preference configuration for every household would substantially increase the number of control combinations and the complexity of the present simulation. Therefore, the same priority structure is applied to all households in this study.

BESS discharge is selected as the first curative action because it can immediately reduce household grid import, subject to the available battery state of charge and discharge-power limits, without initially reducing the EV charging power requested by the user. EV curtailment is activated only when the available BESS support is insufficient to restore the transformer and feeder currents below their respective thresholds. The adopted sequence therefore follows a lexicographic operational principle: available local storage flexibility is used first, while EV charging limitation is treated as a fallback action. The present study does not claim that this ordering is optimal or near-optimal under every grid condition. Alternative priority sequences, household-specific preferences, battery-degradation considerations, and sensitivity of the results to the selected ordering should be investigated in future work.

If congestion remains after the available BESS support has been applied, one of three curative EV-control strategies is activated. All controlled scenarios share the same BESS-first configuration and differ only in the allocation of the subsequent EV curtailment. This common configuration enables a controlled comparison of the EV-allocation strategies but does not isolate the individual contributions of BESS-only and EV-only control; corresponding ablation cases are left for future work. The investigated scenarios are described below.

The batched strategy limits selected groups of households instead of curtailing all controllable EVs on the affected feeder simultaneously. A persistent batch pointer advances the starting batch after each congestion event so that the same group does not always receive the first intervention. The present analysis reports the number of households affected at the same time and the aggregate curtailment effort, but it does not calculate a quantitative fairness or non-discrimination metric. No claim is made that Scenario 3 is fairer than the feeder-wide alternatives. A formal assessment would require customer-level indicators such as curtailment frequency, duration, curtailed energy, and the relationship between customer characteristics and curtailment exposure, as discussed in [19].

1. **Scenario 1:** No curative EMS intervention (reference case).
2. **Scenario 2:** Simultaneous feeder-wide §14a-style curtailment of all controllable EV charging points.
3. **Scenario 3:** Batched round-robin curtailment in groups of three households.
4. **Scenario 4:** Staged feeder-wide reduction in four steps toward the 4.2 kW limit.

The value of 4.2 kW represents the final lower charging setpoint considered in the present §14a-style control implementation, rather than the only charging setpoint used in all controlled scenarios [3]. Scenario 2 applies this limit directly to all controllable EVs on the affected feeder, while Scenario 3 applies it selectively to successive household batches. Scenario 4 provides a discrete adaptive response to the measured network loading: EV charging setpoints above 4.2 kW are progressively reduced toward this value, while lower original setpoints are not increased. Each subsequent reduction stage is activated only if the measured feeder or transformer current remains at or above its corresponding threshold. Scenario 4 therefore adapts the curtailment level to the remaining congestion severity, but it does not implement continuous transformer-headroom optimization, dynamic pricing, or an optimization-based setpoint calculation.

The stepwise algorithmic descriptions of these control strategies are provided in Tables 4–6.

Table 4. BESS-first congestion mitigation with simultaneous feeder-wide EV-charging curtailment.

Input: Measured transformer current $I_{tr,k}$, measured feeder currents $I_{f,k}$ for all feeders $f \in \mathcal{F}$, transformer congestion threshold $I_{tr,th}$, feeder congestion thresholds $I_{f,th}$, battery state of charge $SOC_{batt}[k]$, minimum battery state of charge SOC_{min} , maximum BESS discharge power P_{dis}^{max} , EV charging-power limit P_{14a} .

Output: BESS dispatch command $P_{batt}[k]$ and EV-charging curtailment commands.

1. Detect congestion at the transformer or feeder level.
2. If $I_{tr,k} \geq I_{tr,th}$ or $\exists f \in \mathcal{F} : I_{f,k} \geq I_{f,th}$, then congestion is present.
3. If congestion is present and $SOC_{batt}[k] > SOC_{min}$, then:
 - 3.1 Discharge the BESS to reduce grid import, subject to P_{dis}^{max} .
 - 3.2 Update the transformer and feeder loading after BESS dispatch.
4. Else, keep the BESS idle.
5. Check whether the congestion has been resolved.
6. If $I_{tr,k} < I_{tr,th}$ and $I_{f,k} < I_{f,th}$ for all $f \in \mathcal{F}$, then:
 - 6.1 End the congestion-management action.
7. Else:
 - 7.1 Apply the EV charging-power limit P_{14a} to all controllable EVs on the affected feeder.
 - 7.2 End the congestion-management action.

Table 5. BESS-first congestion mitigation with batched round-robin EV-charging curtailment.

Input: Measured transformer current $I_{tr,k}$, measured feeder currents $I_{f,k}$ for all feeders $f \in \mathcal{F}$, congestion thresholds $I_{tr,th}$ and $I_{f,th}$, battery state of charge $SOC_{batt}[k]$, minimum battery state of charge SOC_{min} , maximum BESS discharge power P_{dis}^{max} , households with controllable EVs $\mathcal{H}$, batch size N_{batch} , EV charging-power limit P_{14a} , and persistent starting-batch index j_{start} , initialized to 1 for the first congestion event.

Output: BESS dispatch command $P_{batt}[k]$, EV-charging curtailment commands for selected household batches, and updated starting-batch index j_{start} .

1. Detect congestion at the transformer or feeder level.
2. If $I_{tr,k} \geq I_{tr,th}$ or $\exists f \in \mathcal{F} : I_{f,k} \geq I_{f,th}$, then congestion is present.
3. If congestion is present and $SOC_{batt}[k] > SOC_{min}$, then:
 - 3.1 Discharge the BESS to reduce grid import, subject to P_{dis}^{max} .
 - 3.2 Update the transformer and feeder loading after BESS dispatch.
4. Check whether congestion is resolved.
5. If $I_{tr,k} < I_{tr,th}$ and $I_{f,k} < I_{f,th}$ for all $f \in \mathcal{F}$, then:
 - 5.1 End the congestion-management action.
6. Else:
 - 6.1 Divide the controllable households $\mathcal{H}$ into K batches, each containing up to N_{batch} households.
 - 6.2 Set the active batch $j \leftarrow j_{start}$ and the checked-batch counter $n \leftarrow 0$.
7. While congestion is not resolved and $n < K$, do:
 - 7.1 Apply the EV charging-power limit P_{14a} to the controllable EVs in batch j .
 - 7.2 Update the transformer and feeder loading after curtailment.
 - 7.3 Set $n \leftarrow n + 1$.
 - 7.4 If $I_{tr,k} < I_{tr,th}$ and $I_{f,k} < I_{f,th}$ for all $f \in \mathcal{F}$, then:
 - 7.4.1 Set $j_{start} \leftarrow 1 + (j \bmod K)$ for the next congestion event.
 - 7.4.2 End the congestion-management action.
 - 7.5 Else:
 - 7.5.1 Set $j \leftarrow 1 + (j \bmod K)$ and continue with the next batch.
8. If $n = K$ and congestion is still present, then:
 - 8.1 Report unresolved congestion after applying all available batches.
 - 8.2 Set $j_{start} \leftarrow 1 + (j_{start} \bmod K)$ for the next congestion event.
9. Return the BESS command, batch curtailment commands, and updated starting-batch index.

Table 6. BESS-first congestion mitigation with staged EV-charging curtailment.

Input: Measured transformer current $I_{tr,k}$, measured feeder currents $I_{f,k}$ for all feeders $f \in \mathcal{F}$, congestion thresholds $I_{tr,th}$ and $I_{f,th}$, battery state of charge $SOC_{batt}[k]$, minimum battery state of charge SOC_{min} , maximum BESS discharge power P_{dis}^{max} , households with controllable EVs $\mathcal{H}$, original EV charging power $P_{h,k}^0$ and predefined EV charging-power limit P_{14a} .

Output: BESS dispatch command $P_{batt}[k]$ and staged EV-charging curtailment commands.

1. Detect congestion at the transformer and feeder levels.
2. If $I_{tr,k} \geq I_{tr,th}$ or $\exists f \in \mathcal{F} : I_{f,k} \geq I_{f,th}$, then congestion is present.
3. If congestion is present and $SOC_{batt}[k] > SOC_{min}$, then:
 - 3.1 Discharge the BESS to reduce grid import, subject to P_{dis}^{max} .
 - 3.2 Update the transformer and feeder loading after BESS dispatch.
4. Check whether congestion is resolved.
5. If $I_{tr,k} < I_{tr,th}$ and $I_{f,k} < I_{f,th}$ for all $f \in \mathcal{F}$, then:
 - 5.1 End the congestion-management action.
6. Else, initialize the staged curtailment factors:

$$\Gamma \leftarrow \{0.25, 0.50, 0.75, 1.00\}.$$
7. For each curtailment stage $\gamma_\ell \in \Gamma$, do:
 - 7.1 For each controllable household $h \in \mathcal{H}$, compute the staged power command:

$$P_{h,k}^{cmd} \leftarrow P_{h,k}^0 - \gamma_\ell \max(0, P_{h,k}^0 - P_{14a}).$$
 - 7.2 Apply $P_{h,k}^{cmd}$ to the controllable EVs.
 - 7.3 Update the transformer and feeder loading after curtailment.
 - 7.4 If $I_{tr,k} < I_{tr,th}$ and $I_{f,k} < I_{f,th}$ for all $f \in \mathcal{F}$, then:
 - 7.4.1 End the congestion-management action.
8. If congestion is still present after the final curtailment stage, then:
 - 8.1 Report unresolved congestion after applying the maximum available EV-charging curtailment.
9. Return $P_{batt}[k]$ and the final curtailment commands.

The investigated scenarios are summarized in Table 7.

Table 7. Investigated scenarios.

Scenario	Description
Scenario 1	Baseline case without curative EMS intervention.
Scenario 2	BESS-first logic followed by simultaneous feeder-wide §14a-style curtailment of controllable EV charging points.
Scenario 3	BESS-first logic followed by batched round-robin curtailment in groups of three households.
Scenario 4	BESS-first logic followed by staged feeder-wide reduction in four steps toward 4.2 kW.

2.5. Simulation Environment and Data Preparation

The complete network and control system were implemented in MATLAB and Simulink R2024a (The MathWorks, Inc., Natick, MA, USA; <https://www.mathworks.com/>). No physical laboratory or field-measurement instruments were used in this study; all electrical quantities and control signals were obtained from the simulation model. The LV network model includes the MV/LV transformer, the monitored feeders, and household models with inflexible load, EV, HP, PV, and BESS components. The EMS is implemented as a supervisory rule set that monitors current measurements and dispatches mode-dependent control signals to household-level controllers.

The simulations are performed in phasor mode at a nominal frequency of 50 Hz. This representation is suitable because the main objective is to analyze feeder and transformer loading, congestion detection, and supervisory curative control at the distribution-network level rather than electromagnetic transients on very short time scales.

The simulation horizon covers three consecutive days. Day 2 is used as the main observation window because the congestion events and control actions are clearly visible there. Logged signals include feeder currents, transformer current, EV charging powers, representative BESS power and SOC, representative HP electrical power and indoor temperature, and the supervisory congestion and mode signals.

Although EVs, HPs, PV systems, BESS units, and inflexible loads are represented in every household model and contribute to the calculated household and feeder power demand, the curative control action in the present study is restricted to EV charging, in addition to the initial BESS support. EV charging was selected as the controllable demand because it represents a comparatively high-power and directly adjustable residential load and can be limited through an explicit charging-power setpoint. This makes it suitable for evaluating the proposed §14a-oriented curative strategies in a transparent and consistent manner.

Heat-pump flexibility and demand response from other household loads were intentionally excluded from the curative control logic as a simplifying modeling assumption. Their inclusion would require additional device-specific constraints, including indoor-temperature and comfort limits, minimum operating times, thermal storage dynamics, rebound effects, appliance availability, and household preferences. It would also enlarge the controller state and action space, increase the number of possible control combinations, and increase the simulation complexity and execution time. Restricting the controllable demand to EV charging therefore enables the three curtailment-allocation strategies to be compared under identical and interpretable conditions. The presented simulations demonstrate the technical feasibility of the proposed rule-based strategies within the investigated model, but they do not imply that EV-only control is sufficient for every practical grid condition. Extending the framework to coordinated EV, HP, and flexible-load demand response is identified as future work.

The household input data consist of synthetic time series and parameter sets stored in spreadsheet files. Household-specific variables were randomized within predefined technically plausible ranges and subsequently reviewed for consistency before being imported into MATLAB/Simulink. The same profiles, device parameters, network configuration, and observation interval are used in all four scenarios so that differences in the results arise from the applied control strategy rather than from different input data.

The evaluation is deterministic and scenario-based. No Monte Carlo study, randomized repetitions, confidence intervals, or probabilistic uncertainty model are included. The measurement-triggered controller does not require demand or PV forecasts for its curative decisions, but practical operation could still be affected by measurement error, communication delay, device availability, customer behavior, and model mismatch. Accordingly, the reported results establish a controlled comparison for the investigated operating case and should not be interpreted as a statistical robustness assessment.

From a real-time implementation perspective, the adopted structure offers several practical advantages, including deterministic logic, compatibility with fixed-step simulation, traceability of control decisions, and suitability for future validation in real-time simulation or hardware-in-the-loop environments [20].

A practical implementation of the proposed EMS would require access to transformer- and feeder-current measurements, a supervisory controller or edge-computing unit, and a communication path to the participating households. At the household level, the minimum functional requirements are a local EMS or gateway and controllable interfaces to the EV charging point and the BESS inverter. In a new household equipped with interoperable smart meters, controllable charging equipment, and a communication-enabled inverter, the additional implementation effort would mainly consist of software integration, communication configuration, and commissioning; the rule-based algorithm itself does not

require an additional power-conversion stage and has modest computational requirements. In an existing household with legacy equipment, retrofitting may require current or smart meter interfaces, a communication gateway, protocol converters, a controllable EV charging station, or device-specific actuators. Extending the control to HPs and other flexible loads would additionally require compatible control interfaces and the corresponding comfort, safety, and appliance-operation constraints. A monetary cost assessment is outside the scope of this study because the cost depends strongly on the existing metering and automation infrastructure, the selected communication architecture, device interoperability, installation effort, and whether the household is newly constructed or retrofitted. Therefore, the present work identifies the required functional components but does not claim a universal implementation cost.

3. Results

3.1. Baseline Case Without Curative EMS

The uncontrolled baseline is first examined in order to establish the original congestion pattern of the studied system. Figure 3 shows the Feeder 3 current and transformer current for Scenario 1 on Day 2. In the absence of curative control, the Feeder 3 current exceeds its congestion threshold during the evening charging period, which indicates a clear local feeder congestion event. The transformer current also exceeds its threshold, although for a shorter interval. These results establish the reference case against which the controlled scenarios are evaluated.

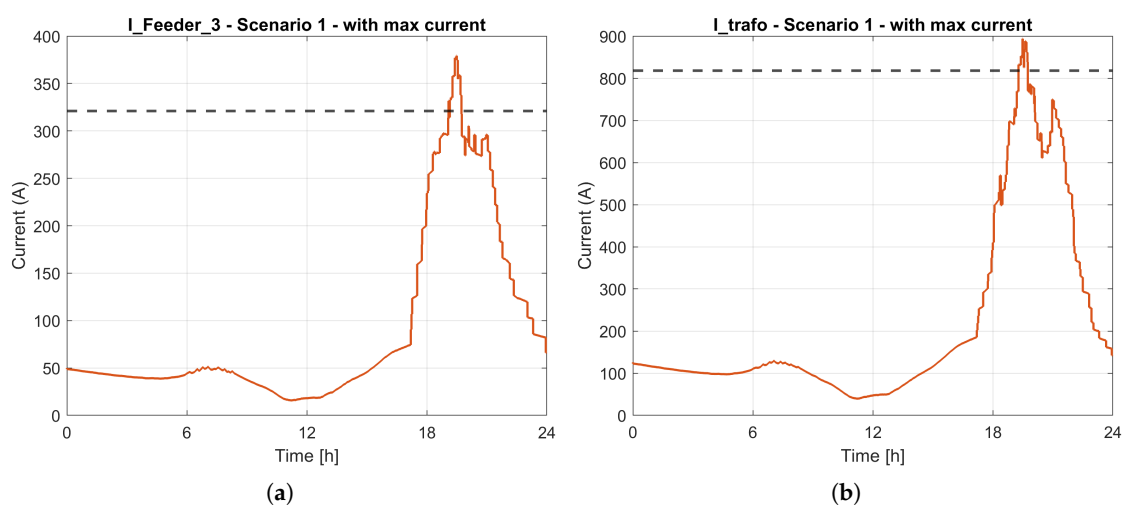


Figure 3. Scenario 1 (no curative EMS): Day 2 current profiles with thresholds: (a) Feeder 3 current; (b) transformer current.

The baseline overload severity is summarized in Table 8. On Feeder 3, the peak current reaches 382.35 A, corresponding to a peak excess of 61.35 A above the congestion threshold of 321 A. The feeder remains above threshold for approximately 1.85 h, leading to an excess area of 62.84 Ah. At the transformer level, the peak current reaches 893.91 A, i.e., 75.91 A above the transformer threshold of 818 A, with a time above threshold of 1.40 h and an excess area of 48.50 Ah. These values quantify the severity of the uncontrolled operating point.

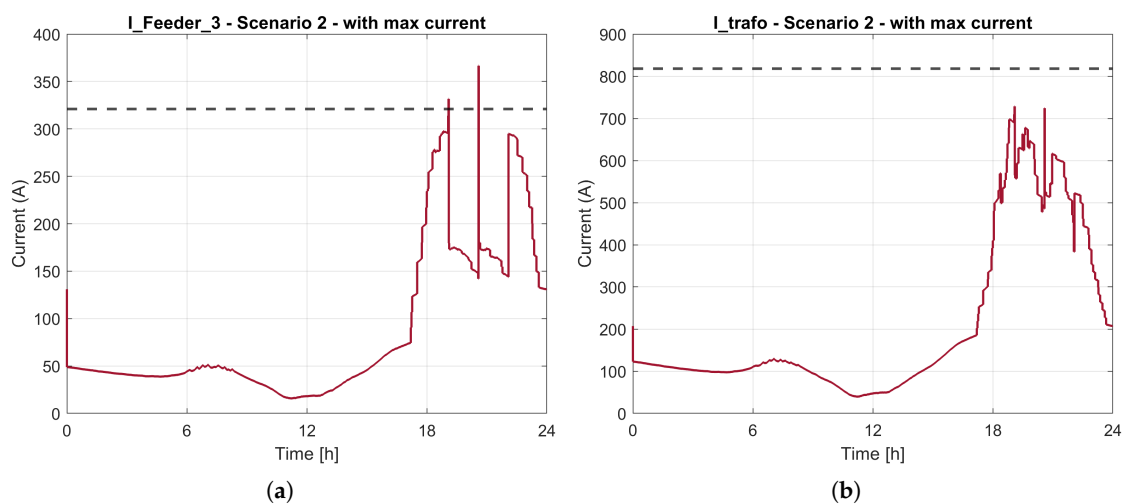
Table 8. Baseline overload severity in Scenario 1 based on the maximum phase RMS currents.

Signal	Limit (A)	Peak Current (A)	Peak Excess (A)	Time Over Limit (h)	Excess Area (Ah)
Feeder 3	321	382.35	61.35	1.85	62.84
Transformer	818	893.91	75.91	1.40	48.50

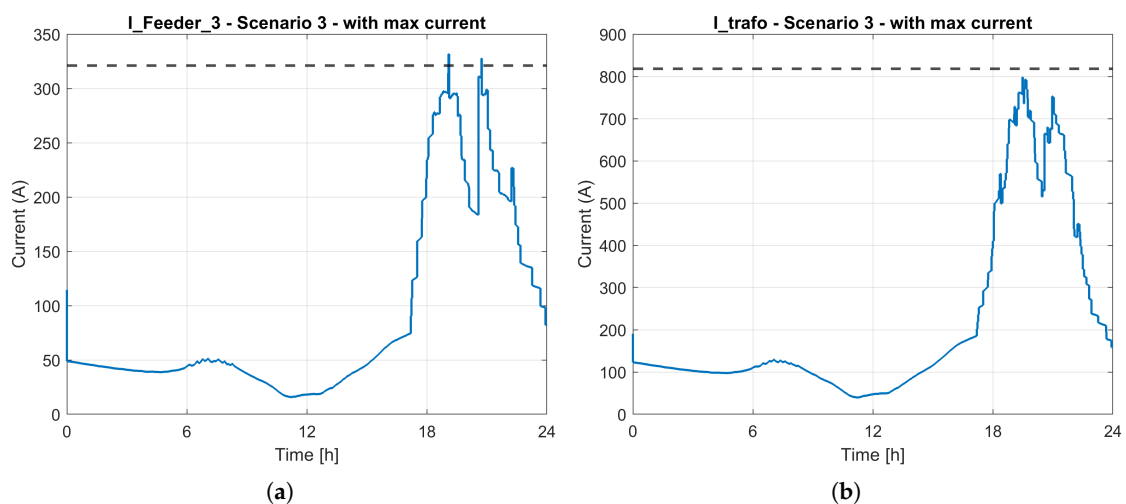
3.2. Response of the Controlled Scenarios

Figures 4–6 present the Day 2 current responses of the three controlled scenarios. In all cases, the proposed EMS reduces both feeder and transformer loading relative to the uncontrolled baseline.

In Scenario 2, shown in Figure 4, the EMS applies simultaneous feeder-wide curtailment to all controllable EV charging points after congestion is detected and BESS support is insufficient. The current reduction is strong and immediate, confirming that simultaneous curtailment is technically effective.

**Figure 4.** Scenario 2: Day 2 current profiles with thresholds: (a) Feeder 3 current; (b) transformer current.

In Scenario 3, shown in Figure 5, EV curtailment is applied in batches of three households using a round-robin logic. The feeder current is reduced significantly, while the transformer current remains somewhat higher than in Scenario 2. This indicates that the strategy relieves the local feeder bottleneck while preserving more upstream network utilization.

**Figure 5.** Scenario 3: Day 2 current profiles with thresholds: (a) Feeder 3 current; (b) transformer current.

In Scenario 4, shown in Figure 6, feeder-wide reduction is applied in multiple stages toward the 4.2 kW cap. The current response is smoother than in Scenario 2 because the controller escalates step by step rather than applying the full limitation immediately.

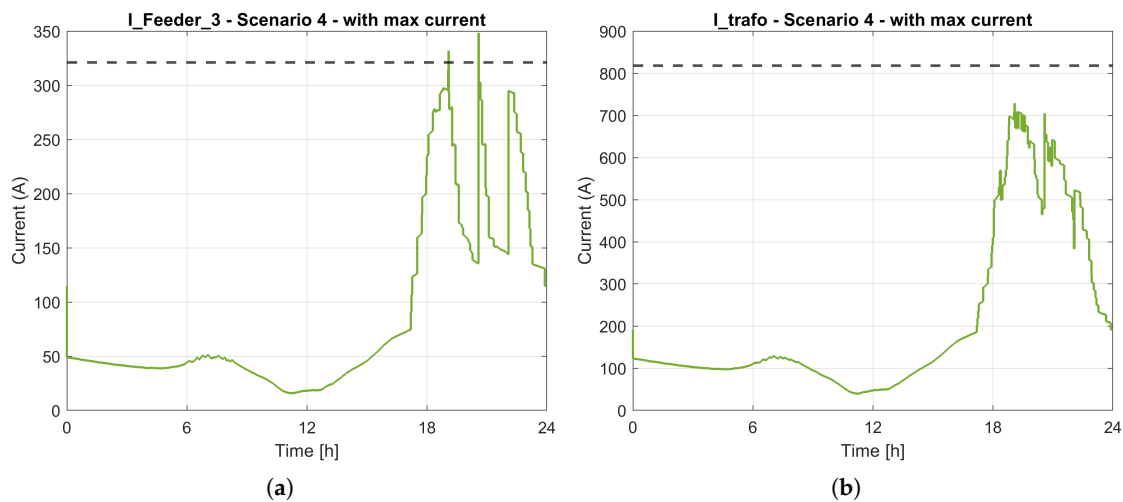


Figure 6. Scenario 4: Day 2 current profiles with thresholds: (a) Feeder 3 current; (b) transformer current.

3.3. Cross-Scenario Feeder Comparison

Figure 7 compares the feeder currents of all four scenarios on Day 2. The results show that Feeder 3 is the dominant congestion location in the investigated case. In contrast, Feeder 1, Feeder 2, and Feeder 4 remain within their admissible operating ranges and show only limited differences between scenarios. In the uncontrolled case, the peak currents of Feeder 1, Feeder 2, and Feeder 4 are 199.72 A, 133.18 A, and 199.72 A, respectively, which are all well below the feeder congestion threshold of 321 A. Relative to Scenario 1, the peak current changes on these non-congested feeders are only about 7.01 A to 12.15 A, and no excess above the threshold occurs in any of the controlled cases. This confirms that the proposed EMS primarily addresses a local feeder bottleneck rather than a uniform network-wide overload.

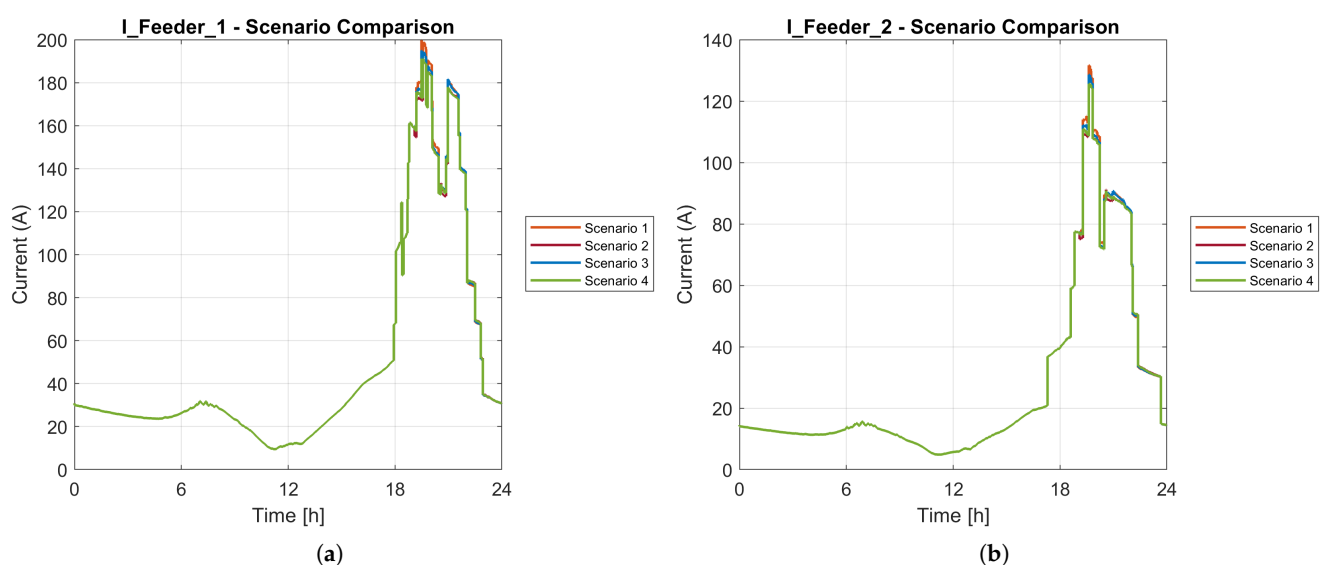


Figure 7. Cont.

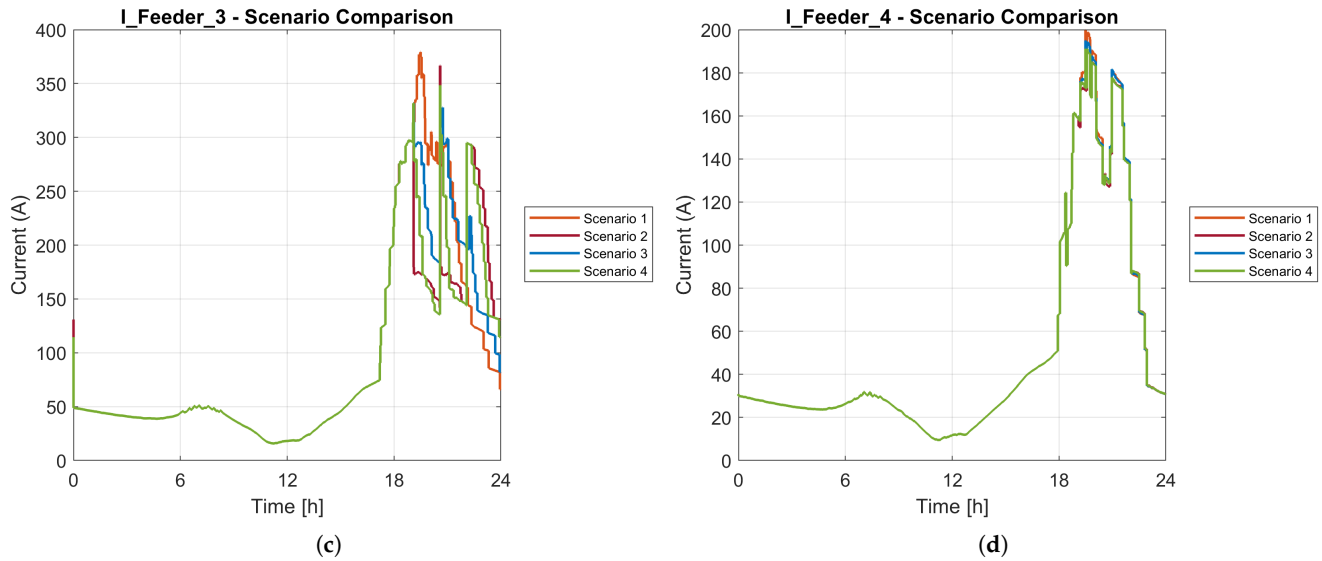


Figure 7. Cross-scenario comparison of feeder currents for Day 2: (a) Feeder 1; (b) Feeder 2; (c) Feeder 3; (d) Feeder 4.

3.4. Quantitative Scenario Comparison

To compare the control strategies quantitatively, the current reduction of each controlled scenario $s \in \{2, 3, 4\}$ is evaluated relative to the uncontrolled baseline Scenario 1 using time-aligned simulation outputs. The feeder-current reduction is not an independently commanded quantity and is not obtained from a fixed power-to-current conversion. Instead, it is calculated during post-processing from the simulated maximum phase RMS current traces. At every simulation time step, the controlled feeder current is subtracted from the corresponding baseline feeder current under the same input profiles and observation interval. Negative differences are set to zero so that only an actual reduction relative to the baseline is counted. For the critical feeder, the instantaneous curtailed current is therefore defined as

$$\Delta I_{F3,t}^{(s)} = \max(0, I_{F3,t}^{(1)} - I_{F3,t}^{(s)}), \quad (18)$$

and similarly for the transformer,

$$\Delta I_{tr,t}^{(s)} = \max(0, I_{tr,t}^{(1)} - I_{tr,t}^{(s)}). \quad (19)$$

From these signals, the peak-current reduction is obtained as

$$\Delta I_{\text{peak},F3}^{(s)} = \max_t \Delta I_{F3,t}^{(s)}, \quad \Delta I_{\text{peak},tr}^{(s)} = \max_t \Delta I_{tr,t}^{(s)}, \quad (20)$$

and the cumulative curtailed current is defined as

$$J_{F3}^{(s)} = \int_{T_{\text{obs}}} \Delta I_{F3,t}^{(s)} dt, \quad J_{tr}^{(s)} = \int_{T_{\text{obs}}} \Delta I_{tr,t}^{(s)} dt, \quad (21)$$

where T_{obs} denotes the observation interval, here Day 2.

In the discrete simulation, the cumulative curtailed current is evaluated numerically as $J_{F3}^{(s)} = \frac{\Delta t}{3600} \sum_k \Delta I_{F3,k}^{(s)}$ and analogously for the transformer, where Δt is the simulation sample interval in seconds. Division by 3600 converts the accumulated ampere-seconds to ampere-hours. Thus, the reported cumulative reduction corresponds to the area between the time-aligned baseline and controlled current traces over Day 2.

A complementary overload-severity metric is the area above threshold, defined for Feeder 3 and the transformer as

$$A_{F3}^{(s)} = \int_{T_{\text{obs}}} \max(0, I_{F3,t}^{(s)} - I_{F3,\text{th}}) dt, \quad (22)$$

and

$$A_{\text{tr}}^{(s)} = \int_{T_{\text{obs}}} \max(0, I_{\text{tr},t}^{(s)} - I_{\text{tr},\text{th}}) dt. \quad (23)$$

For a more direct comparison of all four scenarios, two additional key performance indicators are calculated from the overload and curtailment areas. The feeder-overload mitigation rate is defined as $M_{F3}^{(s)} = 100(1 - A_{F3}^{(s)} / A_{F3}^{(1)})$, where Scenario 1 has $M_{F3}^{(1)} = 0\%$. For the controlled cases, the feeder-relief efficiency is defined as $E_{F3}^{(s)} = (A_{F3}^{(1)} - A_{F3}^{(s)}) / J_{F3}^{(s)}$. This dimensionless indicator expresses the removed feeder-overload area per unit of cumulative feeder-current reduction. It is an intervention-efficiency indicator for the common simulation window and should not be interpreted as an economic efficiency or cost metric. The transformer-overload mitigation rate is calculated analogously.

The corresponding numerical results are summarized in Table 9. Scenario 1 is included explicitly as the reference case; its curtailed-current values are zero by definition, while its residual-overload values equal the uncontrolled excess areas. On Feeder 3, Scenario 2 yields the strongest intervention, with a peak curtailed current of 205.06 A and a cumulative curtailed current of 977.34 Ah. Scenario 4 follows with a peak curtailed current of 186.10 A and a cumulative curtailed current of 816.00 Ah. Scenario 3 is less intrusive, with a peak curtailed current of 109.71 A and a cumulative curtailed current of 328.54 Ah. At the transformer level, the same ranking of intervention magnitude is observed.

Table 9. Numerical comparison of all four scenarios based on the maximum phase RMS currents. Curtailment values are evaluated relative to Scenario 1; residual values denote the remaining overload area.

Scenario	F3 Peak (A)	F3 Curtail. (Ah)	F3 Residual (Ah)	Transformer Peak (A)	Transformer Curtail. (Ah)	Transformer Residual (Ah)
Scenario 1	0.00	0.00	62.84	0.00	0.00	48.50
Scenario 2	205.06	977.34	0.64	231.51	1061.25	0.00
Scenario 3	109.71	328.54	0.82	116.99	360.85	0.00
Scenario 4	186.10	816.00	0.64	210.93	888.31	0.00

Table 10 converts these quantities into directly comparable KPIs. All three controlled scenarios remove at least 98.70% of the Feeder 3 overload area and 100% of the transformer overload area within the reported numerical precision. Scenarios 2 and 4 both achieve a Feeder 3 mitigation rate of 98.98%, while Scenario 3 achieves 98.70%. However, Scenario 3 requires only 328.54 Ah of cumulative feeder-current reduction, compared with 977.34 Ah for Scenario 2 and 816.00 Ah for Scenario 4. This corresponds to 66.38% less cumulative intervention than Scenario 2 and 59.74% less than Scenario 4. Scenario 4 requires 16.51% less intervention than Scenario 2 while reaching the same residual feeder-overload area.

The resulting feeder-relief efficiencies are 0.064, 0.189, and 0.076 for Scenarios 2, 3, and 4, respectively. Consequently, Scenario 2 provides the largest instantaneous reduction, and Scenario 4 provides the same residual overload as Scenario 2 with a smoother and less intensive intervention. Nevertheless, Scenario 3 provides the highest overload relief per unit of cumulative feeder-current reduction and is therefore the most balanced strategy under the KPIs evaluated in this study.

Table 10. KPI-based comparison of overload mitigation and intervention efficiency for all four scenarios.

Scenario	F3 Residual (Ah)	F3 Mitigation (%)	F3 Curtail. (Ah)	Relief Efficiency (-)	Transformer Residual (Ah)	Transformer Mitigation (%)
Scenario 1	62.84	0.00	0.00	–	48.50	0.00
Scenario 2	0.64	98.98	977.34	0.064	0.00	100.00
Scenario 3	0.82	98.70	328.54	0.189	0.00	100.00
Scenario 4	0.64	98.98	816.00	0.076	0.00	100.00

3.5. EV Charging, BESS, and Supervisory Signals

In Scenario 1, many charging traces remain above the 4.2 kW reference line because no curative limitation is applied. In Scenario 2, many traces are clipped at the reference level, reflecting simultaneous feeder-wide curtailment. In Scenario 3, fewer EVs are curtailed at the same time, which is consistent with the batch-based control logic. In Scenario 4, the charging power approaches the 4.2 kW limit in a more gradual manner due to staged reduction.

Figure 8 shows three representative EV charging profiles for each of the four scenarios. These plots illustrate the different intervention mechanisms more clearly. Scenario 2 reduces charging directly to the curtailment level, Scenario 3 limits only selected EVs at a given time, and Scenario 4 applies discrete staged reductions.

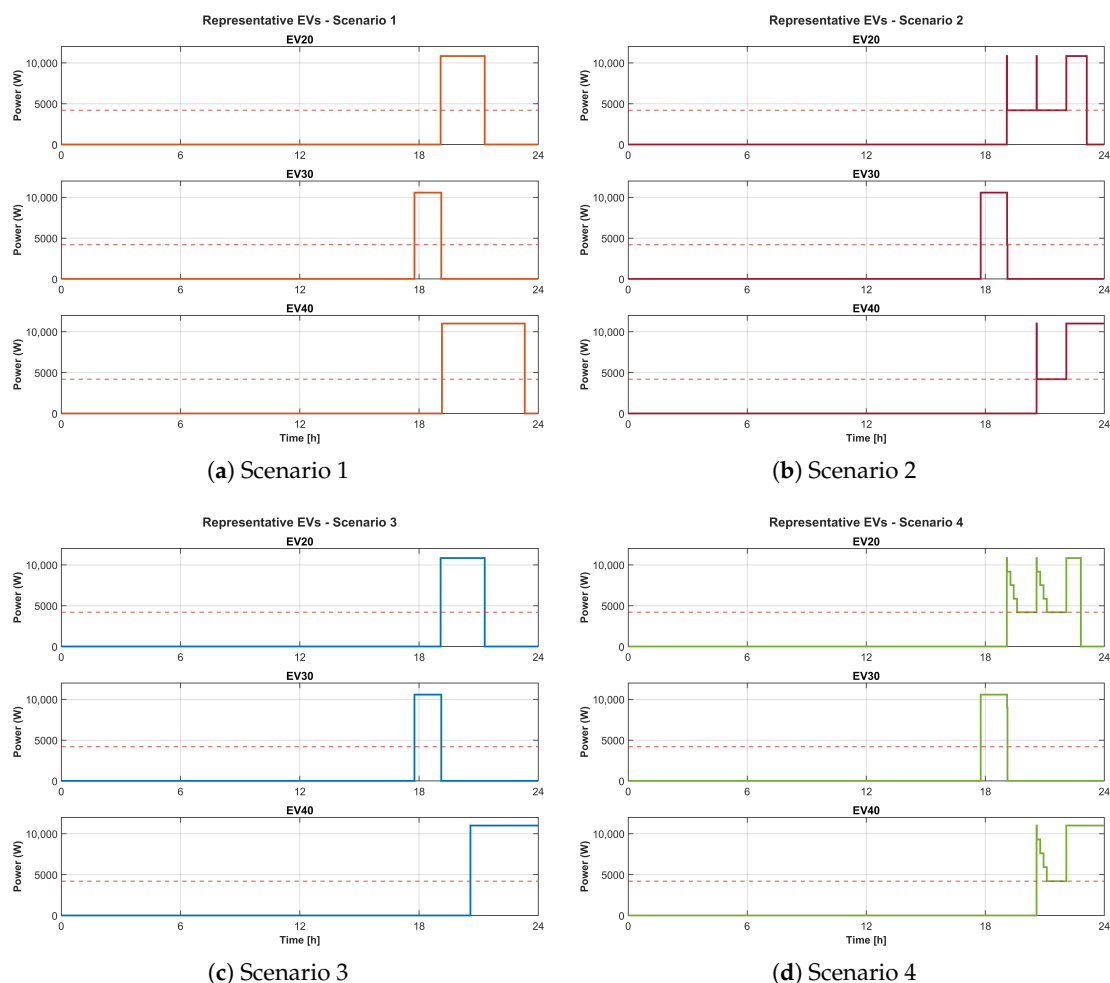


Figure 8. Representative EV charging profiles on Day 2 for the four investigated scenarios. The dashed line marks the 4.2 kW reference level.

Finally, Figure 9 shows the congestion signal and the corresponding mode signal of the EMS. The congestion signal identifies threshold violations, while the mode signal indicates whether the supervisory controller remains in congestion mode. Their close correspondence confirms that the supervisory control logic operates consistently.

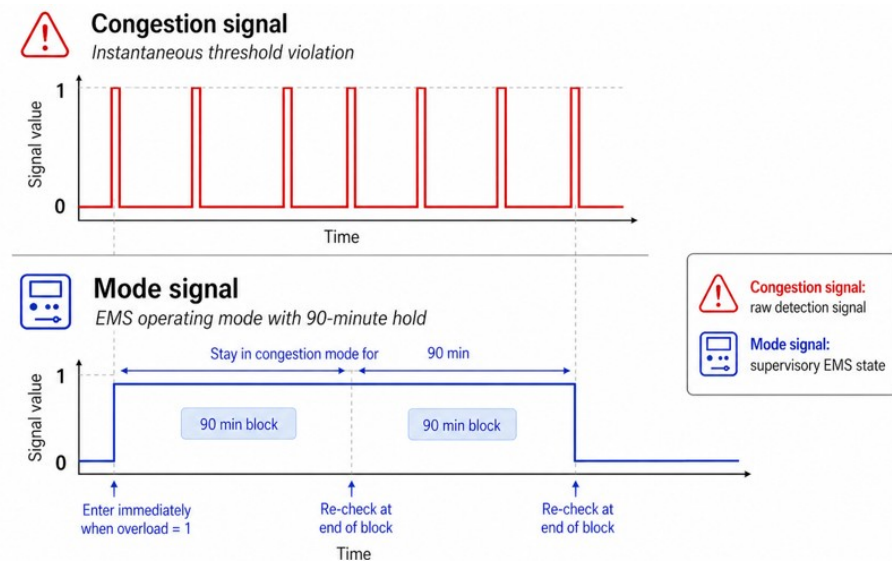


Figure 9. Supervisory signals for congestion detection and EMS mode selection.

4. Discussion

The investigated operating point produces a clear current-based congestion event, with Feeder 3 acting as the dominant local bottleneck. Scenario 1 serves as the internal no-control benchmark because it uses the same network, household profiles, device parameters, and observation interval as the controlled cases. Scenario 2 provides a second, deliberately conservative reference by applying the §14a-style charging limit simultaneously to all controllable EVs on the affected feeder after the available BESS support proves insufficient. Scenarios 3 and 4 can therefore be compared with both the uncontrolled operating point and the direct feeder-wide limitation under identical simulation conditions.

This internal benchmark is distinct from a numerical comparison with an external EMS based on OPF, MPC, stochastic optimization, or learning. Such approaches generally use different objective functions, forecasts, constraints, network models, control horizons, and datasets; consequently, published numerical values cannot be compared directly with the present results. A rigorous external benchmark would require implementing the alternative controllers on the same network with the same device models, congestion events, and KPIs. This comparison is outside the scope of the present work and remains an important direction for future research.

All three controlled scenarios mitigate the overload, but their intervention characteristics differ. Scenario 2 produces the largest instantaneous reduction, with a Feeder 3 peak reduction of 205.06 A, but also the largest cumulative feeder-current reduction of 977.34 Ah. Scenario 4 reaches the same residual Feeder 3 overload area as Scenario 2 while using 16.51% less cumulative feeder-current reduction and providing a smoother staged response. Scenario 3 removes 98.70% of the Feeder 3 overload area and 100% of the transformer overload area within the reported numerical precision while requiring only 328.54 Ah of cumulative feeder-current reduction. Its feeder-relief efficiency is 0.189, compared with 0.064 for Scenario 2 and 0.076 for Scenario 4. Under the KPIs evaluated here, Scenario 3 therefore provides the most balanced trade-off between technical congestion relief and intervention intensity for the investigated case.

The scope of customer intervention must be distinguished from fairness. Scenarios 2 and 4 apply feeder-wide control and can affect all controllable EVs on the congested feeder during an intervention. Scenario 3 instead activates curtailment for groups of three households and therefore affects fewer customers simultaneously. This observation describes the breadth of intervention only; it does not establish a fairer or non-discriminatory allocation. The study does not calculate customer-level indicators such as curtailment frequency, curtailment duration, curtailed energy, or the relationship between customer characteristics and curtailment exposure. A formal assessment based on such indicators, as discussed in [19], requires multiple congestion events and is reserved for future work.

Rebound behavior is also relevant because reducing EV charging power extends the charging period for a fixed energy requirement. Under a simplified constant-power approximation, the charging time is

$$t_{\text{ch}} \approx \frac{E_{\text{req}}}{\eta_{\text{ch}} P_{\text{ch}}}, \quad (24)$$

where E_{req} is the required charging energy, η_{ch} is the charging efficiency, and P_{ch} is the charging power. Reducing charging from 11 kW to 4.2 kW increases the idealized charging time by a factor of approximately $11/4.2 \approx 2.62$. Curtailment can therefore shift demand to later periods and may create secondary synchronization effects [21,22]. Both feeder-wide strategies may be exposed to synchronized rebound because they coordinate many EVs simultaneously, whereas the batched strategy may distribute the deferred demand across smaller groups. However, the present study does not quantify post-curtailment rebound peaks or delayed charging completion, so this interpretation should be treated as a qualitative consideration rather than a demonstrated performance result.

The rule-based structure has several disadvantages. It cannot guarantee a globally optimal solution, and its performance depends on predefined thresholds, priority rules, batch size, and staged setpoints. It is less adaptive than optimization-based or learning-based approaches when operating conditions depart from those anticipated during controller design. Practical operation also depends on sufficiently reliable measurements, communication, and device actuation. Moreover, the current implementation considers only current-based thermal constraints, one dominant congested feeder in a radial network, no ring operation, and a no-export assumption. Voltage magnitude, voltage unbalance, reactive power, simultaneous multi-feeder congestion, and transformer-level coordination of competing feeder requests are not evaluated.

Further limitations concern flexibility modeling and validation. The curative demand-side action is restricted to EV charging, although HPs and other loads are included in the household models. The BESS and EV representations omit several deployment-relevant effects, including battery degradation, inverter apparent-power limits, ramp rates, thermal constraints, state-dependent power capability, and variable efficiency. The BESS-first sequence is evaluated as a predefined priority, without BESS-only, EV-only, EV-first, or combined-control ablation cases. In addition, the study uses one deterministic set of synthetic profiles and does not include Monte Carlo repetitions, confidence intervals, systematic sensitivity analysis, field-data benchmarking, or a direct comparison with an external controller implemented on the same test system. These assumptions support a transparent comparison of the investigated strategies but limit the statistical generalizability and deployment readiness of the results.

5. Conclusions

This paper presented a rule-based EMS for curative congestion management in a low-voltage residential grid within a §14a EnWG-oriented setting. The two-layer archi-

texture combines measurement-based transformer and feeder congestion detection with household-level BESS support and scenario-dependent EV charging control. The controller was implemented in MATLAB/Simulink and evaluated using an uncontrolled baseline, simultaneous feeder-wide curtailment, batched round-robin curtailment, and staged feeder-wide reduction.

All three controlled scenarios substantially mitigate the investigated overload, but they differ in intervention intensity. The simultaneous strategy provides the largest immediate current reduction. The staged strategy reaches the same residual feeder-overload area with 16.51% less cumulative feeder-current reduction than simultaneous control. The batched strategy removes 98.70% of the feeder-overload area and 100% of the transformer overload area within the reported numerical precision while requiring only 328.54 Ah of cumulative feeder-current reduction. Its feeder-relief efficiency of 0.189 exceeds the values of 0.064 and 0.076 obtained for the simultaneous and staged strategies, respectively. The batched strategy is therefore the most balanced option for the investigated deterministic case when technical congestion relief and intervention efficiency are considered together. This conclusion does not constitute a quantitative fairness or non-discrimination assessment.

The main disadvantages of the proposed method are its lack of global optimality, dependence on predefined thresholds and priorities, limited adaptability to untested operating conditions, and reliance on measurement, communication, and device-control infrastructure. The present validation is additionally limited to current-based congestion, one dominant feeder in a radial network, EV-focused curative demand control, simplified storage and EV models, and one deterministic set of synthetic profiles without statistical uncertainty analysis or an external controller benchmark.

Future work should evaluate wider operating conditions and repeated congestion events; perform systematic sensitivity, uncertainty, and ablation analyses; include customer-level fairness indicators; coordinate simultaneous multi-feeder and transformer congestion; incorporate voltage, unbalance, reactive-power, comfort, degradation, and inverter constraints; extend control to HPs and other flexible loads; and compare the rule-based EMS directly with optimization-based and learning-based controllers on the same test system. Real-time simulation, hardware-in-the-loop testing, field-data benchmarking where data-access conditions permit, and a detailed techno-economic implementation assessment are also required before deployment.

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Abbreviations

BESS	Battery energy storage system
COP	Coefficient of performance
DRL	Deep reinforcement learning
DSO	Distribution system operator
EMS	Energy management system
EnWG	Energiewirtschaftsgesetz (German Energy Industry Act)
EV	Electric vehicle
HP	Heat pump
IEA	International Energy Agency
KPI	Key performance indicator
LV	Low voltage
MPC	Model predictive control
MV/LV	Medium voltage/low voltage
NAYY	Cable designation for an aluminum-conductor power cable with polyvinyl chloride insulation and sheath
OPF	Optimal power flow
PV	Photovoltaic
RL	Reinforcement learning
RMS	Root mean square
SOC	State of charge
TD3	Twin delayed deep deterministic policy gradient

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