Zero Trust Defense Against Charge Manipulation Attacks in Smart EV Charging Infrastructure

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The Sixteenth International Conference on Smart Grids, Green Communications and IT Energy-aware Technologies
ENERGY 2026

Biography:

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Research Interests:

- ✓ electric vehicle charging systems
- ✓ cybersecurity in power systems
- ✓ security and privacy in IoT applications
- ✓ machine learning

Main Outlines

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02 **Threat Model**

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1 Motivation & Problem Statement

Rapid Growth

EV charging stations are expanding rapidly in scale and network complexity [1]

Cloud Dependence

Backend management via cloud APIs and remote protocols introduces new attack surfaces [2]

Protocol Risk

OCPP 1.6/2.0.1 protective features can be bypassed with elevated access [3]

Perimeter Failure

Traditional boundary-based models cannot protect dynamic, distributed EVCS [4]

Key Challenge

- No session-level protocol enforcement
- Static trust with no real-time updates
- No charger-side behavioral detection
- OCPP misuse goes undetected
- Evolving threats bypass perimeter

2 Threat Model: Charge Manipulation Attacks

Adversaries possess moderate-to-advanced resources including access to compromised credentials, mobile apps, and backend interfaces [5,6].

DEMAND SURGE

- Simultaneously initiate large-scale charging
- Destabilizing grid demand spikes
- Man-in-the-Middle session injection
- Exploits weak/static authentication

COORDINATED SWITCHING

- Periodic on/off cycling of chargers
- Triggers inter-area oscillations
- Concealed via FDIA on telemetry
- Uses tampered firmware/scheduler

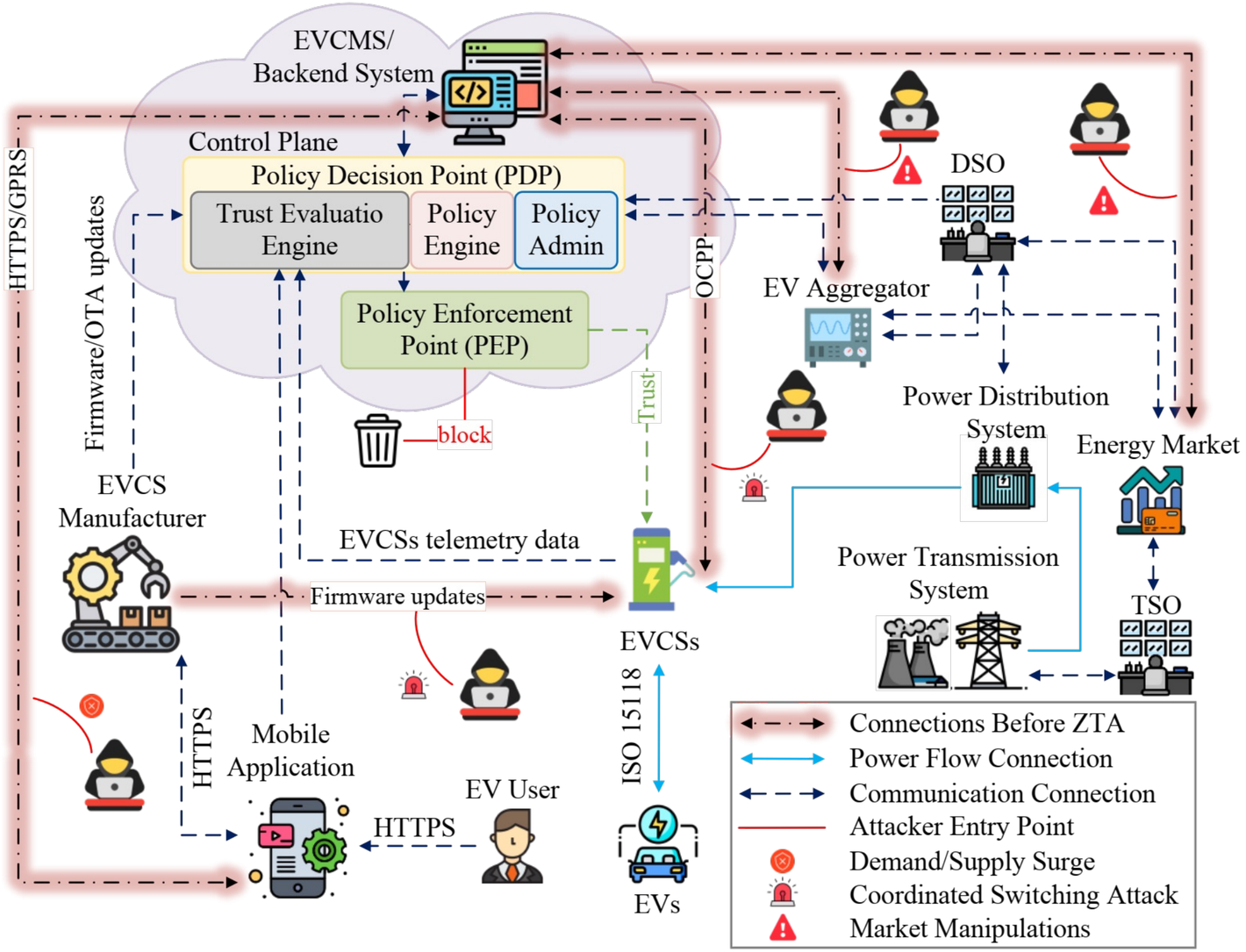
MARKET MANIPULATION

- Distort price signals and trading
- Inject false load data into aggregators
- Exploit EVCMS or aggregator APIs
- Spoofed measurement values

All attack types exploit protocol weaknesses and can bypass perimeter-based security → ZTA is required

3 Proposed ZTA Framework: System Architecture

Core Principle:
No charging request is trusted by default
every interaction is evaluated in real-time based on behavioral context, device integrity, and protocol activity.



4 Trust Evaluation: Three Behavioral Dimensions

Stability Degree (SD)

Weight: 0.4

Evaluates consistency of charger communication connection disruptions and request timeouts

$$T_s^{(t)} = T_s^{(t-1)} + ((V_l + \lambda_l \cdot l_s) \cdot (T_l - l_s)) + ((V_r + \lambda_r \cdot r_s) \cdot (T_r - r_s))$$

- l_s, r_s = connection disruptions, request timeouts
- V_l, V_r = penalty weight for connection disruptions/request timed out
- T_l, T_r = maximum allowable threshold for distruption/timeouts
- Rapid penalty when thresholds exceeded

Intimacy Degree (ID)

Weight: 0.3

Quantifies historical interaction strength between charger and cloud management platform

$$T_i^{(t)} = T_i^{(t-1)} + (q_i + \eta_1 R_t + \eta_2 R_t')(R_t' - R_t)$$

- R_t = percentile rank of interaction
- q_i = fluctuation control parameter (moderates sensitivity to minor rank changes)
- Decreased activity → reduced trust
- Stable/improved frequency → accumulation

Abnormality Degree (ED)

Weight: 0.3

Captures deviations: protocol misuse, unauthorized commands, geographic inconsistencies

$$T_e^{(t)} = \begin{cases} T_e^{*(t)} + \sum_{i=1}^{N} Q(\text{Exception}_i), & N \neq 0 \\ T_e^{*(t)} - p_e, & N = 0 \end{cases}$$

- $Q(.)$ = severity score per anomaly
- p_e = recovery coefficient
- Fine-grained contextual penalization

Global Trust Score: $T_n^{(t)} = w_s \cdot T_s^{(t)} + w_i \cdot T_i^{(t)} - w_e \cdot T_e^{(t)}$ where $w_s + w_i + w_e = 1$

4 Markov-Based State Update Process

Each trust dimension is modeled as a discrete-time Markov chain with 5 trust states, enabling probabilistic prediction of charger behavior.

Bayesian Belief Update

$$\pi_d^{(t)} = \frac{P_d^\top \cdot \left(\pi_d^{(t-1)} \odot \mathcal{O}_d(z_d^{(t)})\right)}{\left\| P_d^\top \cdot \left(\pi_d^{(t-1)} \odot \mathcal{O}_d(z_d^{(t)})\right) \right\|_1}$$

$\boldsymbol{\pi_d^{(t)}}$ = belief distribution over 5 states
p_d = stationary Markov transition matrix
$\boldsymbol{O_d(z_d^{(t)})}$ = observation likelihood vector

Trust Score Computation & Authorization

$$T_d^{(t)} = \pi_d^{(t)} \cdot \mathbf{v}_d$$

$$\mathbf{v}_d = [0.0, 0.25, 0.5, 0.75, 1.0]^\top$$

Each 3-hour evaluation window updates all trust dimensions.
Authorization decision:

$$K_n^{(t)} = JWT\ issued\ if\ T_n^{(t)} \geq \tau\ (threshold = 70)$$

5 Policy Enforcement & OCPP 2.0.1 Integration

Policy Enforcement Point (PEP) Workflow

1. Intercept OCPP 2.0.1 request from EVCS
2. Parse message & inspect embedded JWT token
3. Verify scope, expiration & signature integrity
4. Check $r_i^{(t)} \in \mathscr{A}(\mathscr{P}, \kappa)$ → allowable actions
5. Accept or block & flag mismatch
6. Validated the token and request $\mathrm{Verify}(\sigma_{\mathrm{firm}}, K_{\mathrm{pub}}^{\mathrm{PDP}}) = \mathtt{True}$

Key Properties & OCPP Controls

- All EVCS messages routed through PEP
- JWT: short-lived, cryptographically signed
- Session-level verification per request
- The request requires PDP authorization
- Digital signature check before the implementation of command
- Context-aware enforcement for CMAs

Only chargers with $T_n^{(t)} \geq \tau$ receive access tokens

6 Simulation Setup & Methodology

Chargers	Evaluation Windows	Attack Rate	Protocol
5 (A–E)	**10**	**30%**	**OCPP 2.0.1**
Real-world dataset 2 outlets each	Each = 3-hour peak period	Sessions injected with CMA	Python emulation All messages valid

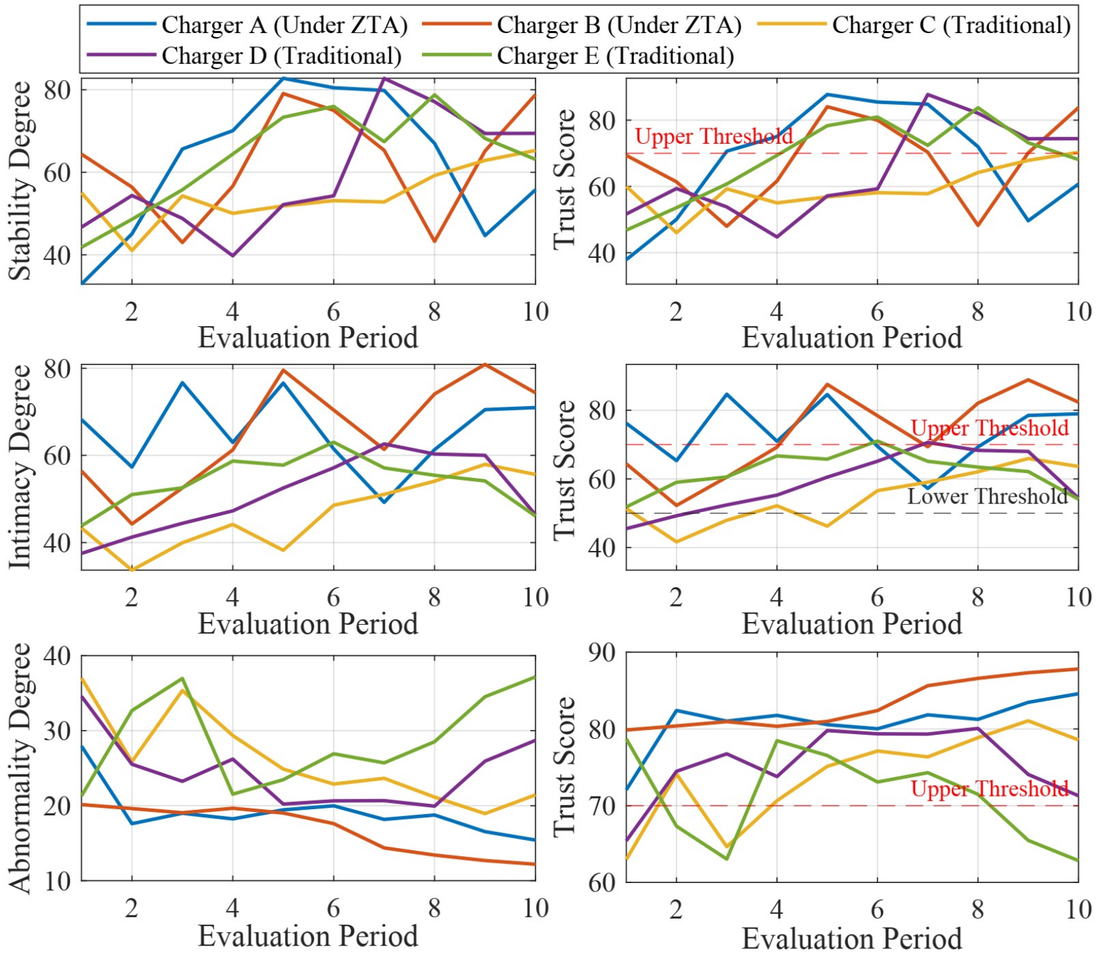
TRUST LEVEL HIERARCHY

Trust Level	Controlling Measure	Permission	Trust Score Range
I	N/A	Monitored access	[90,100]
II	Downgrading permissions	Restricted access; Monitored access	[70,90)
III	Re-authenticating	Access temporarily denied	[50,70)
IV	Blocking connections	Access denied	[0,50)

Attack Injection Strategy

- Modified: energy requested & charging duration
- Syntactically on valid OCPP 2.0.1 messages
- Randomized across chargers & time windows
- Mimics stealthy, coordinated behavior
- Designed to evade rule-based detection

6 Results: Trust Score Evolution Under Attack



ZTA Observation (A & B)

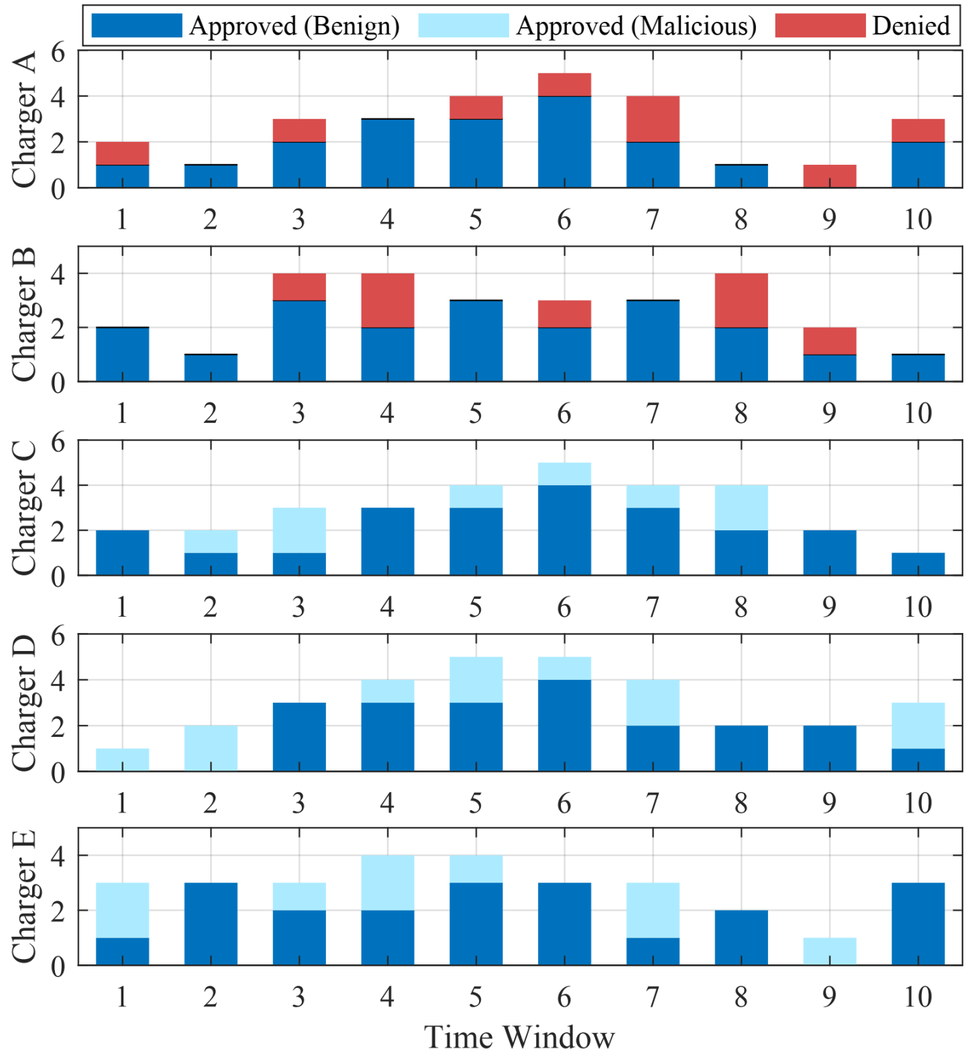
Sessions denied when trust drops below Level II threshold (≥70). Proactive access control prevents attack propagation.

Traditional Observation (C, D, E)

Trust score degrades similarly, but no enforcement occurs→all sessions, including malicious ones are approved regardless of behavioral anomalies.

ZTA enforcement threshold (τ = 70) separates Trust Level II from Level III — triggering re-authentication or denial.

6 Results: Access Control Effectiveness and Computational Overhead & Scalability



ACCESS CONTROL EFFECTIVENESS UNDER CMA

Charger Type	Approved	Denied	Denial Rate
A (ZTA-enabled)	19	8	100%
B (ZTA-enabled)	20	7	87.5%
C (Traditional)	30	0	0.0%
D (Traditional)	31	0	0.0%
E (Traditional)	29	0	0.0%

Key Finding

ZTA-enabled chargers blocked 87.5–100% of malicious sessions.
Traditional chargers approved 100% regardless of attack.

Trust Score Update (per charger)	JWT Token Verification (PEP)	Session Init Latency
120–150 ms	**2–5 ms**	**Seconds**
Every 3-hour window Intel Xeon E5-2680 v4, 8 GB RAM	Per session request Signature validation overhead	Token overhead negligible vs. typical session timing

7 Conclusion

Novel ZTA Framework

Continuous behavioral assessment of EVCS with dynamically issued trust tokens based on real-time indicators

Markov-Based Trust Model

State-aware probabilistic tracking of Stability, Intimacy & Abnormality dimensions across 5 trust states

OCPP 2.0.1 Integration

Session-level enforcement via PEP with JWT tokens; firmware validated by PEP before OTA deployment

Validated Effectiveness

87.5–100% malicious session detection vs. 0% for traditional models under coordinated CMA scenarios

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THANKS

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