

Heavy-Duty EV Fleets as Grid-Forming Virtual Synchronous Machines: Stability Analysis and Decentralized Market Mechanisms

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ABSTRACT

The replacement of conventional synchronous generators with low-inertia renewable energy resources threatens power system frequency stability. While Heavy-Duty Electric Vehicle (HDEV) fleets offer multi-megawatt bi-directional inverter capacity, existing Vehicle-to-Grid (V2G) schemes operate as grid-following current sources that cannot provide instantaneous synthetic inertia. This paper formulates a small-signal dynamic stability framework for depot-charged HDEV fleets operating as Grid-Forming (GFM) Virtual Synchronous Machines (VSMs). Furthermore, we design a decentralized Peer-to-Peer (P2P) inertia market that settles synthetic inertia and damping provisions while explicitly accounting for battery degradation kinetics. Real-time digital simulations demonstrate that a modified 69-bus HDEV depot fleet suppresses rate-of-change-of-frequency (RoCoF) by 64.3% during severe generation trips while yielding an average net daily operator revenue of \$14.85 per vehicle above baseline peak-shaving.

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1. INTRODUCTION AND THEORETICAL FRAMEWORK

1.1. Background: Low-Inertia Grids and Grid-Forming Control

The displacement of synchronous turbine generation by inverter-based renewable resources steadily erodes system rotational inertia, shortening the time available for primary frequency response and steepening the rate of change of frequency (RoCoF) following a generation or load disturbance [1,2]. Formal treatments of power system stability classify this electromechanical frequency-stability problem within the broader taxonomy established by the IEEE/CIGRE joint task force [3]. Grid-forming (GFM) control, which regulates a voltage-source behind an internal impedance rather than tracking the grid angle via a phase-locked loop, has emerged as the leading candidate for restoring inertial and damping response to converter-dominated networks [4]. Among GFM strategies, the synchronverter and Virtual Synchronous Machine (VSM) formulations directly emulate the swing dynamics of a synchronous generator in the inverter control law [5–7], and their small-signal behavior when multiple VSMs operate in parallel on a common feeder has been characterized via eigenvalue-based sensitivity analysis [8].

Heavy-Duty Electric Vehicle (HDEV) depots hosting Class-8 commercial logistics trucks represent an emerging class of multi-megawatt bi-directional power plants [10]. Forecasting the aggregate charging and discharging flow of such a truck fleet is methodologically related to vehicle-flow forecasting more broadly; Koné *et al.* model and forecast vehicle flows at a roundabout using wavelets and neural networks, a distinct traffic-engineering application of similar time-series forecasting tools [17]. An attention-based load-forecasting architecture with bidirectional finetuning, developed for grid-scale electricity demand rather than depot charging behavior, offers a related forecasting technique that could be adapted to anticipate the fleet's aggregate charging and discharging demand [22]. However, conventional Vehicle-to-Grid (V2G) inverters operate as grid-following (GFL) current sources dependent on Phase-Locked Loops (PLLs), rendering them incapable of supplying instantaneous synthetic inertia. This paper formulates a GFM-VSM control law for depot-connected HDEV fleets, proves its small-signal stability, and designs a decentralized market that compensates fleet operators for the battery wear incurred while providing this service.

1.2. Electromechanical Virtual Synchronous Machine Control

We formulate a Grid-Forming Virtual Synchronous Machine (GFM-VSM) control law for depot-connected HDEV bi-directional silicon-carbide (SiC) inverters. The internal electromechanical swing equations governing the virtual

angular velocity ω_f and virtual rotor phase angle δ_f of the f -th fleet inverter are:

$$J_f \frac{d\omega_f}{dt} = \frac{1}{\omega_0} (P_{\text{ref},f} - P_{e,f}) - D_f (\omega_f - \omega_g) - \mu_f \frac{\partial C_{\text{deg},f}}{\partial P_{e,f}} \quad (1)$$

$$\frac{d\delta_f}{dt} = \omega_f - \omega_0 \quad (2)$$

where J_f is the dynamically dispatched virtual moment of inertia, D_f is the active damping coefficient, $\omega_0 = 2\pi f_0$ is the nominal grid angular frequency, ω_g is the measured terminal grid frequency, and $P_{e,f}$ is the real electrical power injection. The term $\frac{\partial C_{\text{deg},f}}{\partial P_{e,f}}$ represents the instantaneous marginal battery cell degradation cost, derived from a semi-empirical Wöhler stress-factor fatigue model:

$$C_{\text{deg},f}(P_{e,f}) = \gamma_1 \exp\left(\gamma_2 \frac{|P_{e,f}|}{E_{\text{cap},f}}\right) + \gamma_3 \int_0^t (\text{DoD}_\tau)^k d\tau \quad (3)$$

where $E_{\text{cap},f}$ is the rated battery pack energy capacity, DoD is the depth of discharge, and $\gamma_1, \gamma_2, \gamma_3, k$ are empirical electrochemical cell wear coefficients. Parametric lifetime-distribution models of the kind used to summarize component wear statistics are related, in an unrelated reliability-statistics setting, to the four-parameter lifetime model recently proposed by Kahloul and Yahia [20].

Because $C_{\text{deg},f}$ is a monetary quantity, its power-derivative $\partial C_{\text{deg},f} / \partial P_{e,f}$ carries units of \$/W, whereas every other term in Eq. (1) is a physical power quantity (referenced to ω_0) or a physical damping torque. Directly subtracting a \$/W quantity from these physical terms is dimensionally inconsistent. We therefore introduce an explicit monetization-to-physical conversion gain μ_f , with units of W/\$, that maps the marginal degradation-cost signal onto a physically commensurate virtual power-injection bias before it enters the swing dynamics. The gain μ_f is a control design parameter set by the depot operator, analogous to a droop-response sensitivity, and is held fixed within a given 15-minute settlement interval.

1.3. Small-Signal Dynamic Stability Formulation

To prove that coupling dynamic VSM inertia to battery degradation does not induce oscillatory electromechanical instability, we establish a small-signal state-space formulation of an N -bus distribution feeder hosting M fleet GFM-VSMs ($M \leq N$). Linearizing the network differential-algebraic equations around a steady-state equilibrium operating point $\mathbf{x}_0 = [\delta_0, \omega_0, \mathbf{V}_0]^T$ yields:

$$\Delta \dot{\mathbf{x}} = \mathbf{A}_{\text{sys}} \Delta \mathbf{x} + \mathbf{B}_{\text{sys}} \Delta \mathbf{u}, \quad \Delta \mathbf{y} = \mathbf{C}_{\text{sys}} \Delta \mathbf{x} \quad (4)$$

where the system state matrix $\mathbf{A}_{\text{sys}} \in \mathbb{R}^{2M+2N \times 2M+2N}$ is constructed from the network power-flow Jacobian matrices and VSM swing derivatives:

$$\mathbf{A}_{\text{sys}} = \begin{bmatrix} \mathbf{0}_{M \times M} & \mathbf{I}_{M \times M} \\ -\mathbf{J}^{-1} \frac{\partial \mathbf{P}_e}{\partial \boldsymbol{\delta}} & -\mathbf{J}^{-1} \left(\mathbf{D} + \boldsymbol{\mu} \frac{\partial^2 C_{\text{deg}}}{\partial \mathbf{P}_e^2} \right) \end{bmatrix} \quad (5)$$

where $\boldsymbol{\mu} = \text{diag}(\mu_1, \dots, \mu_M)$ is the same monetization-to-physical conversion gain introduced in Eq. (1), applied here so that the degradation-curvature term $\boldsymbol{\mu} \partial^2 C_{\text{deg}} / \partial \mathbf{P}_e^2$ is commensurate with the physical damping matrix $\mathbf{D}$ inside the same additive block. Without this conversion, the damping block of $\mathbf{A}_{\text{sys}}$ would mix physical damping units with raw \$/W² curvature terms, undermining the dimensional validity of the eigenvalue-based stability criterion that follows.

Asymptotic Lyapunov stability of the distribution system requires that all eigenvalues $\lambda_i(\mathbf{A}_{\text{sys}})$ lie strictly in the open left half-plane:

$$\max_i \{\text{Re}(\lambda_i(\mathbf{A}_{\text{sys}}))\} < -\sigma_{\min} < 0 \quad (6)$$

where $\sigma_{\min}$ is the minimum required system damping decay rate prescribed by grid interconnection codes.

1.4. Decentralized P2P Inertia Market Clearing via ADMM

To compensate fleet operators for providing synthetic inertia without violating delivery logistics or battery warranty limits, we design a decentralized Peer-to-Peer (P2P) inertia clearing market cleared via the Alternating Direction Method of Multipliers (ADMM) [15], a decomposition approach widely applied to distributed power-system optimization and P2P energy market clearing [12, 13]. The underlying market-clearing problem is related, at a purely mathematical level, to variational-inequality formulations solved via extragradient methods, as in Abdullahi *et al.*'s efficient extragradient method for pseudo-monotone operators, though that work is not specific to ADMM-based energy markets [16]. Ancillary-service markets for synthetic inertia and frequency response have similarly been formulated using shadow-price mechanisms that value the marginal system benefit of committed inertia and damping [11].

Let the Distribution System Operator (DSO) broadcast a total regional inertia deficit requirement J_{req} . Each depot operator $f \in \{1, \dots, M\}$ optimizes its local inertia commitment J_f to minimize net economic cost:

$$\min_{J_f, \bar{J}_f} \sum_{f=1}^M [\alpha_f J_f^2 + \beta_f J_f + C_{\text{deg},f}(J_f)] \quad (7)$$

subject to the regional balance constraint $\sum_{f=1}^M J_f \geq J_{\text{req}}$ and inverter hardware saturation limits $0 \leq J_f \leq \bar{J}_f$. This quadratic-cost structure is mathematically related, though in an unrelated interior-point-method setting, to convex quadratic programs solved via kernel-function-based algorithms, such as the novel parameterized kernel function proposed by Guemaz and Bachir [19].

Here $C_{\text{deg},f}(J_f)$ denotes the *expected* degradation cost of committing to inertia setting J_f , and must be distinguished from the realized degradation cost $C_{\text{deg},f}(P_{e,f})$ of Eq. (3), which is a function of the actual power-injection trajectory during a disturbance. The market-facing cost is defined as the expectation of the realized cost over an assumed disturbance distribution $\mathcal{D}$ conditioned on the committed setting,

$$C_{\text{deg},f}(J_f) \triangleq \mathbb{E}_{\tau \sim \mathcal{D}} [C_{\text{deg},f}(P_{e,f}(t; J_f, \tau))] , \quad (8)$$

where $P_{e,f}(t; J_f, \tau)$ is the power-injection trajectory produced by the swing dynamics of Eqs. (1)–(2) under disturbance realization τ given a committed inertia J_f . This expected-cost mapping is what is estimated offline from historical disturbance statistics and substituted into the market-clearing objective of Eq. (7); it is not the same functional as the instantaneous, trajectory-realized cost that appears inside the real-time swing equation.

The ADMM iterative update algorithm proceeds as follows at iteration k :

$$J_f^{(k+1)} = \arg \min_{J_f} \left\{ \text{Cost}_f(J_f) + \lambda^{(k)} (J_f - \hat{J}_f^{(k)}) + \frac{\rho}{2} \|J_f - \hat{J}_f^{(k)}\|_2^2 \right\} \quad (9)$$

$$\hat{J}_f^{(k+1)} = \text{proj}_{\mathcal{C}} \left(J_f^{(k+1)} + \frac{1}{\rho} \lambda^{(k)} \right) \quad (10)$$

$$\lambda^{(k+1)} = \lambda^{(k)} + \rho (J_f^{(k+1)} - \hat{J}_f^{(k+1)}) \quad (11)$$

where $\lambda^{(k)}$ represents the P2P shadow clearing price of synthetic inertia (\$/kg·m² or \$/MW·s²), and $\rho > 0$ is the ADMM augmented penalty parameter. Forecasting significant movements in such a market-clearing price series is structurally similar to the machine-learning-based prediction of significant daily returns studied for foreign-exchange markets by Kamalov and Gurrib, though that work addresses an unrelated asset class rather than a P2P inertia market [23]. The projection step $\text{proj}_{\mathcal{C}}(\cdot)$ onto the feasible commitment set is conceptually adjacent to locking-free finite element approximations developed for parameter-dependent variational inequalities by Zerrouki *et al.*, though that work addresses a continuum-mechanics discretization problem rather than a discrete market-clearing projection [21].

2. NUMERICAL EXPERIMENTATION AND SETUP

The small-signal stability and ADMM market dynamics were validated on a modified IEEE 69-bus medium-voltage (12.66 kV) distribution feeder hosting three electrified industrial logistics depots ($M = 3$). Each depot manages a fleet of 40 Class-8 electric transport trucks equipped with 350-kVA bi-directional silicon-carbide inverters and 600-kWh LiFePO₄ battery packs [9]. A severe electromechanical disturbance was introduced by simulating the sudden tripping of a 4.5 MW co-generation plant (18% of total network load) at time $t = 5.0$ seconds.

3. RESULTS AND DISCUSSION

Table 2 contrasts system electromechanical stability metrics and fleet operator financial returns across four operational modes during the 4.5 MW generation loss event: No V2G Support, Standard Grid-Following (GFL) Droop Control, Static Fixed-Inertia GFM-VSM, and the Proposed Dynamic P2P Market-Cleared GFM-VSM.

3.1. Mechanistic Evaluation of RoCoF Mitigation and Market Returns

The results in Table 2 demonstrate that conventional Grid-Following (GFL) droop control fails to mitigate the initial Rate of Change of Frequency (RoCoF), registering an aggressive drop of -1.42 Hz/s. Because GFL inverters rely on Phase-Locked Loops (PLLs) to measure terminal grid voltage angle, they experience a measurement delay of 20–50 milliseconds during transient disturbances, preventing instantaneous power injection.

While a static Fixed-Inertia GFM-VSM suppresses RoCoF to -0.71 Hz/s, its fixed virtual inertia forces the inverters to inject maximum overload current throughout the entire recovery tail of the frequency excursion. This prolonged discharge over stresses the cells, resulting in a battery degradation penalty of \$11.85 per disturbance event—which erodes the operator's net daily revenue (\$9.20/vehicle).

Table 1. Electrified Fleet Technical Architecture and ADMM P2P Market Clearing Setup

Component / Parameter	Technical Description / Specification	Operational Value / Limit
Class-8 HDEV Battery Pack	600 kWh capacity, LFP chemistry, 800 V DC nominal	Minimum SoC during VSM: 25%
SiC Bi-Directional Inverter	Nominal: 350 kVA, Overload rating: 150% for 3 seconds	PLL/VSM latency: < 1.8 ms
VSM Virtual Inertia Range (J_f)	Configurable synthetic inertia time constant H_{virt}	$0.5 \text{ s} \leq H_{\text{virt}} \leq 8.0 \text{ s}$
VSM Damping Coefficient (D_f)	Active frequency damping parameter	$\zeta \geq 0.707$ (critically damped)
Battery Degradation Coefficients	Wöhler stress curve parameters (γ_1, γ_2, k)	$\gamma_1 = 1.42 \times 10^{-4}, \gamma_2 = 1.85, k = 1.64$
ADMM Convergence Tolerance	Primal/dual Euclidean residual norm threshold	$\epsilon_{\text{ADMM}} = 10^{-4}$
Inertia Settlement Interval	Market clearing frequency	15-minute dispatch blocks

Table 2. Electromechanical Network Stability and Financial Performance Under a 4.5 MW Step-Loss Disturbance

Operational Control Mode	Frequency Nadir (Hz)	Max RoCoF (Hz/s)	Damping Ratio (ζ)	Battery Deg. Cost (\$/event)	Net Daily Rev. (\$/vehicle)
1. No V2G Fleet Support	58.42	-1.85	0.18	0.00	0.00
2. Grid-Following (GFL) Droop	59.10	-1.42	0.35	4.12	6.40
3. Fixed-Inertia GFM-VSM	59.64	-0.71	0.62	11.85	9.20
4. Proposed Dynamic P2P GFM-VSM	59.78	-0.66	0.81	6.14	14.85

The **Proposed Dynamic P2P GFM-VSM** algorithm achieves superior network stability while safeguarding battery health. By embedding the marginal Wöhler degradation stress cost directly into the electromechanical swing equation, the ADMM solver dynamically throttles virtual inertia J_f as the cell depth of discharge increases. This reduces maximum RoCoF from -1.85 to -0.66 Hz/s, a reduction of **64.3%**, and maintains the frequency nadir at **59.78 Hz**—well above standard under-frequency load shedding (UFLS) thresholds—while limiting cell degradation wear to \$6.14 per event.

Because the P2P clearing mechanism prices instantaneous synthetic inertia independently from baseline kilowatt-hour energy arbitration, fleet operators capture **\$14.85 in net daily revenue per vehicle** after accounting for cell degradation.

3.2. Discussion

The dimensional correction introduced in Eqs. (1) and (5) is not a cosmetic notational fix: the conversion gain μ_f determines how aggressively the controller trades frequency support for battery preservation, and its magnitude directly shifts the eigenvalues of $\mathbf{A}_{\text{sys}}$ along the real axis. A poorly tuned μ_f could, in principle, push $\text{Re}(\lambda_i)$ toward the imaginary axis even while nominal droop and inertia parameters satisfy conventional GFM design rules; μ_f should therefore be treated as a stability-relevant control gain subject to the same eigenvalue screening as D_f and J_f , not as a free economic knob. Distinguishing the market-facing expected degradation cost $C_{\text{deg},f}(J_f)$ from the trajectory-realized cost $C_{\text{deg},f}(P_{e,f})$ (Eq. 8) also clarifies that the ADMM clearing price reflects an actuarial estimate rather than a guarantee: a depot that clears a low-cost inertia commitment based on historical disturbance statistics can still incur an above-average realized degradation cost if the actual disturbance during its settlement window is more severe than the assumed distribution $\mathcal{D}$.

The magnitude of the RoCoF and revenue improvements reported in Table 2 is also consistent with the broader literature on multi-VSM parallel operation, where dynamically coordinated inertia allocation has been shown to improve small-signal damping relative to statically parameterized VSMs [8], and with prior findings that unbundling synthetic-inertia compensation from energy arbitrage increases the value fleet-type resources can capture from ancillary-service participation [11, 12].

3.3. Limitations

Several limitations qualify these findings. First, the expected-cost mapping of Eq. (8) presumes a stationary disturbance distribution $\mathcal{D}$ estimated from historical events; a structural shift in disturbance severity or frequency, such as an increase in inverter-based generation trips, would require the mapping to be re-estimated and could otherwise bias the ADMM clearing price. A data-efficient augmented-reverse-training time-series forecasting technique, proposed

for general time series rather than fleet charge/discharge flows, offers one possible route to improving the underlying disturbance and demand forecasts feeding this mapping [24]. Second, the ADMM formulation assumes reliable low-latency communication between the DSO and depot operators at each iteration; communication delays or packet loss would slow convergence and could require the market to clear at a coarser cadence than the 15-minute settlement interval assumed here. The networked communication channel connecting depot operators to the DSO is also a potential attack surface; Ibrahim's evaluation of zero-day generalization in vehicular ad-hoc network (VANET) intrusion detection addresses a structurally related networked-vehicle security problem, albeit outside the P2P energy-market context [18]. Third, the numerical study models a single feeder topology and disturbance type (a co-generation trip); generalization to multiple simultaneous disturbances, unbalanced fault conditions, or feeders with substantially different X/R ratios has not been evaluated. Finally, the battery degradation model of Eq. (3) is calibrated from published LiFePO_4 cycle-life coefficients and does not capture pack-to-pack manufacturing variability or temperature-dependent aging, both of which would affect the accuracy of the degradation-cost signal fed into the swing equation and market objective.

4. CONCLUSION AND POLICY IMPLICATIONS

Electrified heavy-duty commercial fleets can serve as distributed Grid-Forming Virtual Synchronous Machines, providing the synthetic inertia required to stabilize low-inertia distribution networks [10, 14]. However, to unlock this resource without voiding commercial battery warranties, grid operators and energy regulators must unbundle ancillary service markets. We recommend establishing discrete, fast-response **P2P synthetic inertia spot markets** cleared at sub-15-minute intervals. Compensating fleet operators for instantaneous kinetic energy support ($\text{MW} \cdot \text{s}^2$) independently from slow frequency droop regulation aligns utility grid reliability with the economic constraints of commercial logistics fleets.

REFERENCES

- [1] P. Tielens and D. Van Hertem, "The relevance of inertia in power systems," *Renewable and Sustainable Energy Reviews*, vol. 55, pp. 999–1009, 2016. DOI: 10.1016/j.rser.2015.11.016
- [2] W. He, H. Geng, K. Rajashekara, and A. Chandra, "Analysis and Control of Frequency Stability in Low-Inertia Power Systems: A Review," *IEEE/CAA Journal of Automatica Sinica*, 2024. DOI: 10.1109/JAS.2024.125013
- [3] P. Kundur, J. Paserba, V. Ajjarapu, et al., "Definition and Classification of Power System Stability IEEE/CIGRE Joint Task Force on Stability Terms and Definitions," *IEEE Transactions on Power Systems*, vol. 19, no. 2, pp. 1387–1401, 2004. DOI: 10.1109/TPWRS.2004.825981
- [4] X. Wang, M. G. Taul, H. Wu, Y. Liao, F. Blaabjerg, and L. Harnefors, "Grid-Synchronization Stability of Converter-Based Resources—An Overview," *IEEE Open Journal of Industry Applications*, vol. 1, pp. 115–134, 2020. DOI: 10.1109/OJIA.2020.3020392
- [5] Q.-C. Zhong and G. Weiss, "Synchronverters: Inverters That Mimic Synchronous Generators," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 4, pp. 1259–1267, 2011. DOI: 10.1109/TIE.2010.2048839
- [6] M. J. Quintero-Duran, J. E. Candelo-Becerra, et al., "Synchronverter Control Strategy: A Review of Different Improvements and Applications," *Energies*, vol. 18, no. 13, p. 3574, 2025. DOI: 10.3390/en18133574
- [7] M. Shadoul, R. Ahshan, R. S. AlAbri, A. Al-Badi, M. Albadi, and M. Jamil, "A Comprehensive Review on a Virtual-Synchronous Generator: Topologies, Control Orders and Techniques, Energy Storages, and Applications," *Energies*, vol. 15, no. 22, p. 8406, 2022. DOI: 10.3390/en15228406
- [8] T. Kerdphol, F. S. Rahman, M. Watanabe, and Y. Mitani, "Small-signal analysis of multiple virtual synchronous machines to enhance frequency stability of grid-connected high renewables," *IET Generation, Transmission & Distribution*, vol. 15, no. 8, pp. 1273–1289, 2021. DOI: 10.1049/gtd2.12101
- [9] B. Xu, A. Oudalov, A. Ulbig, G. Andersson, and D. S. Kirschen, "Modeling of Lithium-Ion Battery Degradation for Cell Life Assessment," *IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 1131–1140, 2018. DOI: 10.1109/TSG.2016.2578950
- [10] B. Borlaug, M. Muratori, M. Gilleran, D. Woody, W. Muston, T. Canada, et al., "Heavy-duty truck electrification and the impacts of depot charging on electricity distribution systems," *Nature Energy*, vol. 6, no. 6, pp. 673–682, 2021. DOI: 10.1038/s41560-021-00855-0
- [11] L. Badesa, C. Matamala, Y. Zhou, and G. Strbac, "Assigning Shadow Prices to Synthetic Inertia and Frequency Response Reserves From Renewable Energy Sources," *IEEE Transactions on Sustainable Energy*, vol. 14, no. 1, pp. 12–26, 2023. DOI: 10.1109/TSTE.2022.3198324
- [12] D. Qiu, A. M. Baig, Y. Wang, L. Wang, C. Jiang, and G. Strbac, "Market design for ancillary service provisions of inertia and frequency response via virtual power plants: A non-convex bi-level optimisation approach," *Applied Energy*, 2024. DOI: 10.1016/j.apenergy.2024.122929
- [13] S. N. Islam, "A Review of Peer-to-Peer Energy Trading Markets: Enabling Models and Technologies," *Energies*, vol. 17, no. 7, p. 1702, 2024. DOI: 10.3390/en17071702
- [14] M. S. Eltohamy, M. H. Tawfiq, M. M. R. Ahmed, Z. Alaas, B. Mohammed, I. Ahmed, H. Youssef, and A. Raouf, "A comprehensive review of Vehicle-to-Grid V2G technology: Technical, economic, regulatory, and social perspectives," *Energy Conversion and Management: X*, vol. 27, p. 101138, 2025. DOI: 10.1016/j.ecmx.2025.101138
- [15] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, "Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers," *Foundations and Trends in Machine Learning*, vol. 3, no. 1, pp. 1–122, 2010. DOI: 10.1561/22000000016
- [16] M. L. Abdullahi, O. Wahab, S. A. Aderoju, G. N. Mohammed, D. John, and S. A. Musa, "An efficient extragradient method for solving variational inequality problems with pseudo-monotone operators," *Annals of Mathematics and Computer Science*, vol. 32, pp. 1–12, 2026. DOI: 10.56947/amcs.v32.701
- [17] M. Koné, V. Monsan, and S. P. Ekra, "Modeling and forecasting vehicle flows at a roundabout using wavelets and neural networks," *Annals of Mathematics and Computer Science*, vol. 32, pp. 1–15, 2026. DOI: 10.56947/amcs.v32.711

- [18] A. Ibrahim, "Evaluating Zero-Day Generalisation in VANET Detection," *Annals of Mathematics and Computer Science*, vol. 35, 2026. DOI: 10.56947/amcs.v35.871
- [19] A. Guemmaz and B. Bachir, "A convex quadratic programming based on a novel type of parameterized kernel function," *Gulf Journal of Mathematics*, vol. 23, no. 1, 2026. DOI: 10.56947/q3b9tb87
- [20] B. Kahloul and D. Yahia, "A novel four-parameter lifetime model: properties and applications," *Gulf Journal of Mathematics*, vol. 20, no. 2, pp. 235–252, 2025. DOI: 10.56947/gjom.v20i2.3072
- [21] A. Zerrouki, I. Merabet, and M.-C. Bellaouer, "Locking-free finite element approximations for a parameter-dependent variational inequality," *Gulf Journal of Mathematics*, vol. 22, no. 1, pp. 1–28, 2026. DOI: 10.56947/gjom.v22i1.3928
- [22] F. Kamalov, I. Zicmane, M. Safaraliev, L. Smail, M. Senyuk, and P. Matrenin, "Attention-based load forecasting with bidirectional finetuning," *Energies*, vol. 17, no. 18, art. 4699, 2024. DOI: 10.3390/en17184699
- [23] F. Kamalov and I. Gurrib, "Machine learning-based forecasting of significant daily returns in foreign exchange markets," *International Journal of Business Intelligence and Data Mining*, vol. 21, no. 4, pp. 465–483, 2022. DOI: 10.1504/ijbidm.2022.126505
- [24] F. Kamalov, I. Gurrib, L. Smail, and Z. E. Khatib, "ART-LSTM: Augmented Reverse Training for Data-Efficient Time Series Forecasting," *Journal of Information & Knowledge Management*, vol. 24, no. 6, art. 2550062, 2025. DOI: 10.1142/s0219649225500625