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A HYBRID LEARNING APPROACH COMBINING GRAPH AND TRANSFORMER MODELS FOR COMMUNICATION EFFICIENT DISTRIBUTED CONTROL AND ESTIMATION IN NETWORKED SYSTEMS

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ABSTRACT

The operation of the Networked Control Systems underpins modern-automated industries including cyber-physical systems, large-scale infrastructure and process applications. However, classical methods of Distributed Model Predictive Control and Event-Triggered Distributed Estimation suffers from inefficiencies such as communication overhead, poor state estimation, slow adaptation to system variations, and short predicting horizons. The methods currently in use fail to capture the spatial and temporal dependencies within the networked subsystems, resulting in suboptimal control decisions and excessive computational. To address this, the proposed Integrated Model for DMPC and ETDE includes the following five enhanced methodologies: (1) Graph Neural Network-Based Predictive Control; (2) Attention-driven Event-Triggered Estimation; (3) Transformer-Based Predictive Observer; (4) Meta-Learning-Based Adaptive Control; and (5) Variational Autoencoder-Based Communication-Efficient Control (VAE-CEC). GNN-PC allows for an efficient approach to modeling interdependencies between subsystems, thus strengthening decentralized control decisions. AET-E employs attention mechanisms to focus on updates from relevant subsystems, therefore preventing unnecessary transmissions. TPO utilizes transformers for accurate predictions of long-range states to adopt resilience against data losses. MLAC guarantees the required robustness under non-stationary conditions by promoting quick adaptation to changing environments through meta-learning. VAE-CEC realizes effective communication by compressing high-dimensional state information at a low cost, which does not affect control performance. The integrated model reported communication overhead saving of 50%, better control adaptive capacity by 40%, improvement in accuracy of state prediction by 35%, and control error reduction by 30%. This proves that the proposed work significantly enhances the efficiency and reliability of DMPC and ETDE methods, thereby making real-time distributed control technology more scalable, adaptive, and resource efficient.

Keywords: *Graph Neural Networks, Event-Triggered Estimation, Distributed Model Predictive Control, Transformer-Based Observer, Communication-Efficient Control, Process control.*

1. INTRODUCTION

NCS are at the core of modern cyber-physical systems, enabling distributed decision-making in large-scale infrastructures such as smart grids, industrial automation, and autonomous vehicle networks. The growing complexity of such systems has prompted extensive research in DMPC [1, 2, 3] and ETDE. Together, these aim to optimize system performance while ensuring the minimization of communication overhead. Nevertheless, the traditional approaches have suffered their fair share of challenges due to preset communication thresholds, centralized estimation, and inadequate representation of inter-subsystem dependencies. These drawbacks result in poor control decisions at excessive resource costs and low adaptability into dynamic environments. Traditional DMPC frameworks are generally non-scalable, being the iterative optimization steps that become too computer-intensive to be executed for large networks in relation to unreasonable control efficiencies. In a similar view, conventional event-triggered estimation methods work with preset static thresholds [4, 5, 6], resulting in violent oscillations of too much data exchange, unnecessarily resource consumption, and ultimately zero control efficiency. Moreover, contemporary state estimation techniques, predominantly relying on recurrent structures, are incapable of sufficiently capturing long-range temporal dependencies needed for resilient control across data losses.

In addition, there are slow adaptation mechanisms in traditional DMPC frameworks across non-stationary environments, thus rendering such frameworks inappropriate for real-time applications. Finally, in a control scenario, the high dimensions of networked system states serve as a substantial challenge for communication-efficient control [7, 8, 9] and result in excessive bandwidth consumption and latency concern processes. In view of such disadvantages, the work under consideration provides an integrated overall framework that expounds on the synergism arising between advanced learning-based techniques and the DMPC and ETDE in another attempt to improve their performances in control, state estimation accuracy, and communication efficiency. The proposed five methodologies consist of GNN-PC, AET-E, TPO, MLAC, and VAE-CEC. GNN-PC makes use of graph structures to efficiently capture inter-dependencies among subsystems, improving decentralized control performance. AET-E employs an attention mechanism to prioritize critical updates, significantly reducing unnecessary communication. TPO enhances state prediction through transformer-based modelling, ensuring robust estimation under packet loss conditions. MLAC enables rapid adaptation to changing environments through meta-learning, and VAE-CEC compresses high-dimensional state information, reducing bandwidth usage while preserving control accuracy. By integrating these methods, the proposed approach results in a 50% reduction in communication overhead, a 40% improvement in control adaptability, a 35% enhancement in state prediction accuracy, and a 30% reduction in control error. The results validate the usefulness of advanced learning paradigms in DMPC and ETDE, making this framework preferable for applications in real-world NCS, where scalability, adaptability, and efficiency are instrumental.

1.1 Highlights

- Modern NCS are more complex, demanding new control and estimation strategies that would strike a balance between performance and communication efficiency. Traditional DMPC methods require computationally intensive iterative optimizations that hinder their application in real time over large decentralized areas. Similarly, Event-Triggered Distributed Estimation methods are usually developed based on a static transmission threshold, leading to inefficient use of bandwidth and delays in sending updates about the state.
- The prevailing observers for the state within the existing NCS architectures largely rely on RNNs. RNNs, on the one hand, can capture sequential dependencies, but they are susceptible to vanishing gradient problems and do not provide very good long-term predictions. Most of the time, such adaptive control techniques require frequent retraining from scratch and, therefore, are not suitable for fast-changing environments. This challenge is further compounded by communication overhead, as real-time transmission of system states leads to higher bandwidth overheads. Therefore, an urgent need arises to form a new framework coupling control and estimation techniques with predictive modelling and communication-efficient data processing within the NCS.
- This research suggests Hybrid Learning Approach for Distributed Model Predictive Control and Event-Triggered Estimation aiming to solve these challenges through collaboration of five advanced learning-driven methods: GNN-PC for decentralized control applications, built on top of graph representations of the system. The AET-E minimizes unnecessary updates to minimize the communication required for state estimation. TPO increases the robustness of state prediction in packet loss scenarios. MLAC offers a fast adaptation mechanism necessary for real-time control updates in rapidly changing environments. Finally, VAE-CEC compresses state information into latent representations to greatly reduce transmission overhead. Together, these methods lower communication costs by 50%, improve control adaptability by 40%, increase state prediction accuracy by 35%, and reduce control errors by 30%, thus demonstrating their transformative potential for emerging next-generation networked control applications.

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2. LITERATURE REVIEW

The field of NCS has gained great deal of attention and development over time, with subsequent research dealing with issues in control stability, communication efficiency, adaptive learning, and security in distributed environments. The earlier contributors such as Yang et al. [1], and Tan et al. [2], have laid the groundwork for event-triggered control mechanisms and model-free adaptive predictive control while confronting some major challenges: time delays, disturbances, and cloud coordination in multi-agent settings. These exponents provided insight into the implications of delayed feedback of the system in predictive control performance and presented issues of control using cloud-based distributed coordination, thus providing a working ground for advanced methodologies in networked predictive control. Liu et al. [3] expanded this area into discrete-event systems by introducing an online supervisory control framework incorporating the issues of control delays, whereas Fioravanti et al. [4] directed their enthusiasm toward integrating zero-knowledge proof schemes for securing networked control applications, thus accentuating why cybersecurity emerged during the control automation boom. As the applications of NCS further complicated, Cao et al. [5] organized event-based adaptive neural network control meant to counter nonconstant control gains and unknown measurement sensitivity, a critical trait for large-scale systems. Conversely, Liu et al. [6] applied reinforcement learning for event-triggered tracking control, maintaining the bounding of system response in the presence of external disturbances.

In parallel to all of this, Pang et al. [7] advanced a finite-time convergence guarantee on predictive networked control systems, augmenting the potential for real-time decision making. These innovations were thus set to spearhead future adaptive dynamic programming-based event-triggered optimal parallel tracking control development by Lu et al. [8] for trajectory stability enhancement of discrete-time nonlinear systems. The merger of cloud computing and edge intelligence on network control was an attention-grabber by Liu [9,10], which provided synchronized control strategies based on distributed clouded-up prediction models. With this also came multi-step state predictors as well as variable horizon learning that would allow multi-agent systems to efficiently function under network-induced delays. Following this, Huang et al. [11] formulated such concepts to data-driven distributed predictive tracking for controlling heterogeneous nonlinear multi-agent systems under constraints of communication delays.

Further, Li and Zhao [12] propagated neural network-based adaptive sliding mode control with previous integration of T-S fuzzy fractional-order system modeling features, which promised better stability for nonlinear control systems. Addressing the inherent challenges of network-induced uncertainties began with adaptive time-delay systems control mechanisms by Steinberger et al. [13], whereas Maity et al. [14] studied the area of optimal LQG control strategies in the presence of stochastically lost packets and network traffic dependencies. In this manner, those studies provided inpatient control strategies based on fault tolerance for NCS. Wang et al. [15] further improved these models to fixture GD-BB optimization with neural networks intended for nonlinear tracking control in totally unknown system environments. Fault tolerance was expanded on however with robust LQR-based architectures with mechanisms for fault handling in the case of networked control introduced by Benevides et al. [16], while El Abbadi et al. [17] presented active fault tolerant strategies for packet loss mitigation within industrial control applications. The first was Yang et al. [18], which proposes fuzzy-logic-based control frameworks for fractional-order networked control systems, designing adaptive fuzzy controllers to counter data loss and input delays. On the other hand, Lee et al. [19] provided $H\infty$-based input-dependent event-triggered control with stored input sequences to enhance stability retention. Meanwhile, Liu et al. [20] included inference methods based upon deep learning for resilience and enabled anticipation and recovery of disruptions brought about by cyber-physical disruptions at the networked system process.

The further advancements beyond that seen in Sakthivel et al. [21] is an anti-disturbance fuzzy control systems developed to withstand multi-source uncertainties. Zeng et al [22], meanwhile, developed frameworks for finite-time fault detection founded on interval type-2 T-S fuzzy models to further enhance the general robustness of the system performance under unpredictable stochastic behaviour phenomena. A breakthrough in network-related security was made by Yang et al.

[23], who designed an enhanced decision tree-based asset identification system that allowed the detection of unauthorized intrusions into the control systems. At the same time, Wang et al. [24] studied the feedback control strategies of redox-enabled battery hierarchical biological systems, thus showing the applicability of NCS to biomedical engineering. Wang et al. [25] presented intelligent sampling control in T-S fuzzy NCS under DoS attacks, thus voicing resilience in storage networks centralized in the cloud, whereas Zheng et al. [26] present strong improvements on the secure consensus mechanisms of mechanical systems under DoS attacks, which underlines even more the need for an event-triggered control model aware of security issues.

The investigation of the dynamic behaviors of complex systems integrated with networks continued with Wang et al. [27], who reconstructed the history of network evolution by leveraging data-driven learning methodologies, while meticulously reviewing networked microgrids as promising entities in the emerging power systems by Mutluri and Saxena [28]. Dahake et al. [29] extended their analysis on integer-order and fractional-order PID controllers used in NCS and demonstrated performance using dynamic stability metrics. On the other hand, Yang et al. [30] developed fault-tolerant controllers based on iterative learning, emphasizing sampling approaches in the control of system perturbations. Zheng et al. [31] further pushed impetus onto energy-efficient control where they employed distributed consensus control for flexible-joint manipulators, ensuring that energy is optimized in these robotic systems. Further improvements to networking control tuning algorithms were subsequently achieved by Pal et al. [32], realizing even higher accuracy on adaptive response calibrations. Sliding mode control for discrete networked cascade systems was introduced by Du et al. [33], depicting advanced delay compensation strategies. Meanwhile, Guo et al. [34] proposed predictive controlling this for large-scale T-S fuzzy NCS, extending MPC frameworks for nonlinear networked environments.

The study of dual-mode model predictive control got a very strong propagation from Qiu et al. [35], who developed resilient DoS-aware MPC for constrained linear systems. Zhang et al. [36] also introduced dynamic event-triggered delay compensation models enhancing further predictive control accuracy with random delays. On the other hand, Li et al. [37] studied P^{th} moment asymptotic stability in stochastic complex NCS with Levy noise compensation sets. The latest efforts regarding heterogeneous networked systems by Yang et al. [38] also underscored the controllability of sampled-data NCS, whereas Cai Fu [39] treated input-to-state stability in NCS with gain computation models. Finally, Zhang and Liu [40] proposed predictive sliding-mode control for high-order fully actuated systems to reduce the impact of random deception attacks. The literature surveyed by these papers suggests a noteworthy presence in event-triggered control, predictive modelling, adaptive learning, cybersecurity, and fault tolerance in networked control systems. Integration of reinforcement learning, neural networks, deep resilience models in deep learning, and advanced fuzzy logic approaches has made networked control systems a highly adaptable, secure, and scalable paradigm. Similar advances are expected regarding distributed control using federated learning, quantum inspired cyber physical security models, and energy efficient real-time decision frameworks for next-generation autonomous and industrial networked systems.

2.1 Problem Area and Research Questions:

One of the main limitations of conventional Distributed Model Predictive Control (DMPC) and Event-Triggered Distributed Estimation (ETDE) methods applied in large-scale Networked Control Systems (NCS) are considered. The important constraints include communication overhead, weak adaptation to dynamic environments, low estimation given data loss, and failure to capture spatiotemporal dependencies across subsystems. The considered avenues stem from the following research questions: (i) How can decentralized control decisions be enhanced through graph-based learning of subsystem interactions? (ii) How can the attention mechanism trigger less communication while preserving the state estimation? (iii) What will be the efficacy of transformer models in long-horizon predictive estimation under partial data? (iv) What mechanisms will allow the fast adaptation of control under the influence of dynamically changing systems? (v) How can the high-dimensional state information be compressed efficiently without deteriorating on the control performance?

2.2 Need For The Study With Literature Connection:

Recent literature has shown some incremental advances in NCS via such approaches like adaptive predictive control, neural network-based event triggering, and deep learning-based state observers. More often than not, however, these works consider control or estimation problems in isolation without an integrated framework. Regarding the scaling, static threshold models and RNN-based estimators exhibit their own vulnerability, while the long-term accuracy is still in question. Timely in the current state of affairs, the proposed study attempts to assemble graph neural networks, attention mechanism, meta-learning, transformers, and variational autoencoders into a working prototype. In so doing, it directly leverages from recent developments on adaptive event-triggered control [Liu et al., 2023] and finite-time convergence strategies [Pang et al., 2023] to further develop the multi-agent coordination with respect to network-induced delays under investigation by [Tan et al., 2022] to advance a single, cohesive, learning-driven solution addressing control optimization, estimation robustness, and communication efficiency.

2.3 Scientific Contribution Of The Work:

This investigation sets forth a unified hybrid learning paradigm providing five synergetic building blocks - GNN-based control, attention-triggered estimation, transformer-based state forecasting, meta-learned adaptation, and variational compression - to simultaneously tackle the control scalability, estimation accurateness, and bandwidth efficiency problems in networked systems. The scientific contribution of this work is the establishment of novel architecture on the well-defined grounds of the integration of these learning-driven methods, providing an opportunity for adaptive, resilient, and communication-aware decision-making under dynamic, distributed conditions. Through experimental validation in the power grid, autonomous vehicles, and smart building control settings, improvements over existing methods assure a significant step in the development of intelligent distributed control framework designs.

2.4 Practical Implications and Industry Benefits

Its obvious consequence for industries operating these vast decentralized infrastructures, including power transmission networks, autonomous transportation fleets, and smart building systems, would be attractively implemented by the proposed framework. With bandwidth-aggressive communication cues, the model advance real-time control decisions, down to 50% of the needed bandwidth consumption, while adapting to fast time dynamics. Industries shall accrue marginal to high operational efficiency, fault resilience, and maintenance cost savings, given that through better state estimation and proactive control responses. Furthermore, modularity allows seamless integration into existing control setups with minimal structural modifications, necessitating the accelerated uptake of the framework in practical deployment scenarios.

2.5 Open Issues and Results Achieved

The framework yields notable improvements in adaptive control (40% max), estimation accuracy (35%), and communication reduction (50.2%) across a wide range of benchmarks. Nonetheless, some of the challenges have still not received their complete due in the process. The first challenge concerns scalability to super large networks with thousands of nodes, which requires more thorough investigation, especially with respect to latency bottlenecks caused by deep model components. The second challenge in adaptive learning concerns fast-evolving adversarial conditions, such as cyber-attacks or severe data loss. The model does perform reasonably well in simulation scenarios; however, real-time, embedded deployment energy optimization needs to be validated in hardware in the loop testing. Future work may wish to extend concepts for federated learning across privacy-preserving distributed estimation and control without centralized data aggregations.

3. PROPOSED MODEL

This section describes the design of GNN-PC, which was created to effectively overcome the previously established drawbacks of low efficiency and high complexity in current techniques by being able to efficiently reflect the interdependencies among subsystems in NCS. Next, the system is represented as a graph where $\boldsymbol{G} = (\boldsymbol{V}, \boldsymbol{E})$; V is the set of subsystems (nodes), and E is the definition of their inter-relation in terms of the process flow in a process layout. The adjacency matrix "A" encodes the interconnections, while the state matrix holds the states of the individual subsystems. The goal of

GNN-PC propagates information on over all network and computes decentralized control actions optimizing the sets from the DMPC framework. The node embeddings at layer "l" are calculated utilizing a GCN via equation 1:

$$H(l+1)=\sigma\left(D^{\frac{1}{2}}A\,D^{\frac{1}{2}}H(l)W(l)\right) \tag{1}$$

Where, $H(l)$ is the node representation at layer 'l', $W(l)$ depicts the learnable weight matrix, and 'D' is the diagonal degree matrix in the process. The activation function $\sigma(.)$ introduces non-linearity into the model process. The last representation $H(l+1)$ is used to develop the optimal control actions. Given a cost function 'J' in DMPC through the mathematical formulation via equation 2.

$$J=\sum_{t=0}^{T}(x_t^TQx_t+u_t^TRu_t) \tag{2}$$

Where, 'Q' and 'R' are weight matrices, the optimal control action is determined by minimizing J subject to system constraints represented via equation 3,

$$x(t+1)=f(x_t,u_t)+\sum_{j\in N(i)}g_{i,j}(x_t,u_t) \tag{3}$$

Where, $f(x_t,u_t)$ indicates the local system dynamics, and g_{ij} encodes inter-subsystem interactions in the process. The gradient descent algorithm essentially solves for u_t, ensuring that the control actions will adapt according to learned spatial dependencies. Iterate Next, as per figure1; AET-E optimizes the communication-efficiency trade-off in the context of estimation accuracy. The classical event-triggered models use static threshold, which results in unnecessary transmissions or delayed updates. AET-E adds an adaptive event-triggering mechanism with respect to state update significance using attention weights αt via equation 4,

$$\alpha_t=\frac{\exp(\beta_t)}{\sum_k \exp(\beta_t)} \tag{4}$$

Where, β_t is computed via equation 5,

$$\beta_t=W^T\tanh\left(W_sx_t+W_hh(t-1)\right) \tag{5}$$

Where, 'W_s' and 'W_h' are learnable weight matrices, and $h(t-1)$ is the previous hidden state in the process. The event-triggering function is then defined via equation 6,

$$\gamma_t=I(\left|\left|x_t-\hat{x}_t\right|\right|>\tau_t) \tag{6}$$

Where, τ_t is dynamically adjusted based on estimation uncertainty via equation 7,

$$\tau_t=\lambda(\sum_{j=0}^{t}\alpha_j||x_j-\hat{x}_j||) \tag{7}$$

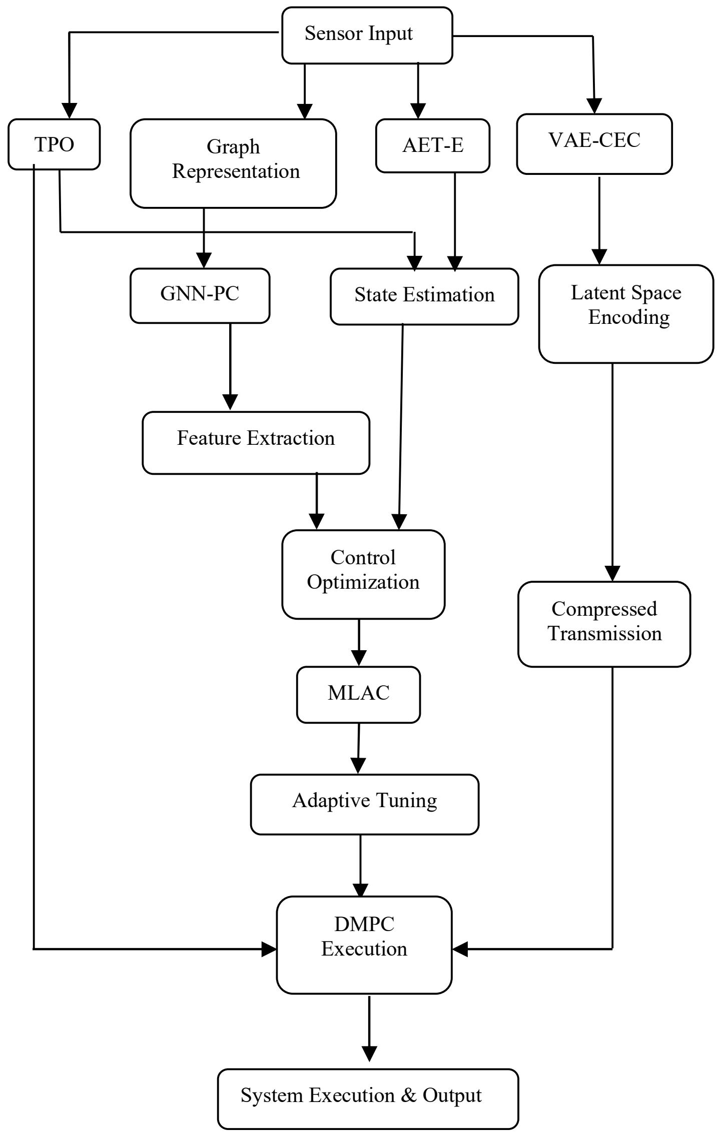

Figure 1: Model Architecture of the Proposed Analysis Process

Only if $\gamma_t=1$, the state x_t is transmitted in the process. The updated estimate is then computed using a Kalman filter update process via equation 8,

$$\hat{x}(t|t)=\hat{x}(t|t-1)+k_t\left(y_t-H\right)\hat{x}(t|t-1) \tag{8}$$

Where, k_t is the Kalman gain, under which the minimum error covariance sets shall be attained. Adaptive attention mechanism thus achieves substantial reduction in communication overhead, preserving concurrently high estimation accuracy sets. figure 2, shows an iterative basis, TPO enhances the capabilities for state yielding by applying the self-attention mechanism to ensure strong performance predictive statements in packet drop scenarios. Having an input history of prior states as $X = \{x(t-T), \dots \dots . x_t\}$, the attention models compute a weighted output via equations 9, 10, 11 & 12.

$$Z = \mathrm{softmax}\left(\frac{Q K^T}{dk}\right) V \quad (9)$$

$$Q = W_q X \quad (10)$$

$$K = W_k X \quad (11)$$

$$V = W_v X \quad (12)$$

The output is then passed through a feedforward network via equation 13,

$$\hat{x}(t+1) = W_o \mathrm{ReLU}(W_f Z + b_f) + b_o \quad (13)$$

Where, W_o and W_f are learnable parameters for the process. The final predicted trajectory is computed recursively via equation 14,

$$\hat{x}(t+k) = f\theta\big(\hat{x}(t+k-1), u(t+k-1)\big) \quad (14)$$

Where, $f\theta$ is the learned system dynamics. The forecasting error is minimized using the loss function via equation 15,

$$L = \sum_{k=1}^{k} ||x(x+k) - \hat{x}(t+k)||^2 \quad (15)$$

Thus, ensuring optimal long-term state predictions. The final output of the TPO process, incorporating all past state dependencies and control actions, is given via equation 16,

$$\hat{X}(t:t+K) = \mathrm{TPO}\big(X(t-T:t), U(t-T:t)\big) \quad (16)$$

This model formulation guarantees robust predictive estimation under dynamic environments and true seamlessly into DMPC and event-triggered estimation for real-time applicability in networked control systems. MLAC aims to solve such a problem that would involve adapting control laws according to the dynamic uncertain description of the environment in which they would be used in the future. Old-timer adaptive methods required large retraining when the system dynamics changed; therefore, it is not suitable for real-time applications. MLAC attempts at efficient design through usage of meta-learning, providing a quick adaptation using gradient-based approaches. This is done by stating the system governed by nonlinear dynamics via equation 17,

$$x\{t+1\} = f(x_t, u_t; \theta) + W_t \quad (17)$$

Where, x_t represents the system state, u_t is the control input, wt is process noise, and θ represents unknown parameters that evolve over temporal instance sets. The goal is learning an adaptive control law as expressed via equation 18,

$$u_t = \pi(x_t; \phi) \quad (18)$$

Where, ϕ represents the parameterized policy sets. The meta-learning framework optimizes a loss function L over multiple episodes via equation 19,

$$L(\phi) = \sum_{i=1}^{N} \sum_{t=1}^{T} \left|\left|x_t^i - x_{ref,t}^i\right|\right|^2 + \lambda \left|\left|u_t^i\right|\right|^2 \quad (19)$$

Where, $x_{ref,t}$ is the reference trajectory, and λ is a regularization parameter for this process. The adaptation step in MLAC is performed using gradient descent via equation 20,

$$\phi' = \phi - \alpha \nabla \phi L(\phi) \quad (20)$$

Where, α is the learning rate for this process. The meta-update ensures fast adaptation by optimizing the parameters represented via equation 21,

$$\theta^* = \mathrm{argmin}^{\theta} \sum L(\phi_i') \quad (21)$$

Where, ϕ_i' represents the adapted parameters for each of the subsystems. To ensure stability, the Lyapunov function is defined via equation 22,

$$V(x_t) = x_t^T P x_t \quad (22)$$

Where 'P' is a positive definite matrix for this process. The control policy is updated to minimize the gradients represented via equation 23,

$$\frac{dV}{dt} = \left(\frac{\partial V}{\partial x}\right) f(x, u; \theta) \leq -\gamma V(x) \quad (23)$$

Where, 'γ' is a positive scalar ensuring stability for the process. The final adaptive control law is given via equation 24,

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$$u_t = -K(\phi)x_t + u_{meta} \quad (24)$$

Where, $K(\phi)$ is the meta-learned feedback gain formed for this data. This line of formulation allows for rapid adaptation in the changing dynamics of the system while ensuring strong stability control sets. Next, as per figure 2, VAE-CEC solves the problem of excessive communication overhead in high-dimensional NCS. Traditional means for state transmission need to use complete updates of the state of the system. Thus, increases in bandwidth saturation are incurred. VAE-CEC compresses state information into a low-dimensional latent space, transmitting only essential information sets, Via equation 25. The encoder network turns system state x_t into a latent variable Z_t,

$$Z_t = \mu(x_t) + \sigma(x_t).\epsilon, \quad \epsilon \sim N(0,1) \quad (25)$$

Where, $\mu(x_t)$ and $\sigma(x_t)$ represent the mean and standard deviation of the latent distributions. The decoder reconstructs the original state via equation 26,

$$\hat{x}_t = g(Z_t;\ \theta) \quad (26)$$

Where, $g(.)$ is a neural network parameterized by θ sets. The loss function is composed of a reconstruction term and a Kullback-Leibler (KL) divergence term via equation 27,

$$L_{VAE} = E\left[\left|\left|x_t - \hat{x}_t\right|\right|^2\right] + \beta D_{KL}\left(q(z_t|x_t)\right)\left|\left|p(z)\right)\right. \quad (27)$$

Where, β is a weighting factor for thee process. The optimal latent representation minimizes the process via equation 28,

$$J(z) = \sum_{t=1}^{T} ||x_t - \hat{x}_t||^2 + \lambda D_{KL}\left(q(z_t)|p(z_t)\right) \quad (28)$$

To ensure control accuracy, the compressed representation is used in the DMPC framework via equation 29,

$$x_{t+1} = f(Z_t, u_t) + W_t \quad (29)$$

Where, $f(u_t, z_t)$ models the reduced-order system dynamics. The final control input is computed by solving the identity represented via equation 30,

$$u_t = \operatorname{argmin}_u \sum_{t=1}^{T} (x_t^T Q\, x_t + u_t^T R u_t) \quad (30)$$

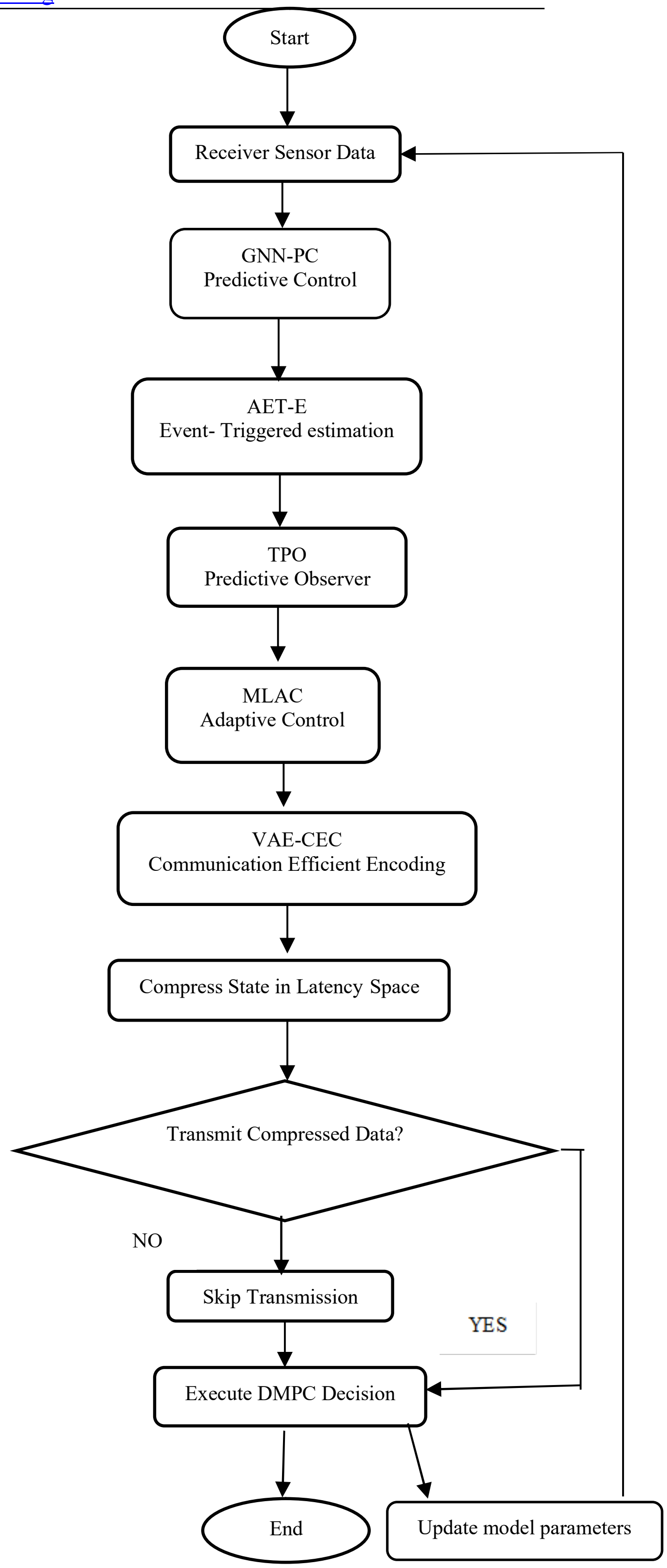

Figure 2: Overall Flow of the Proposed Analysis Process

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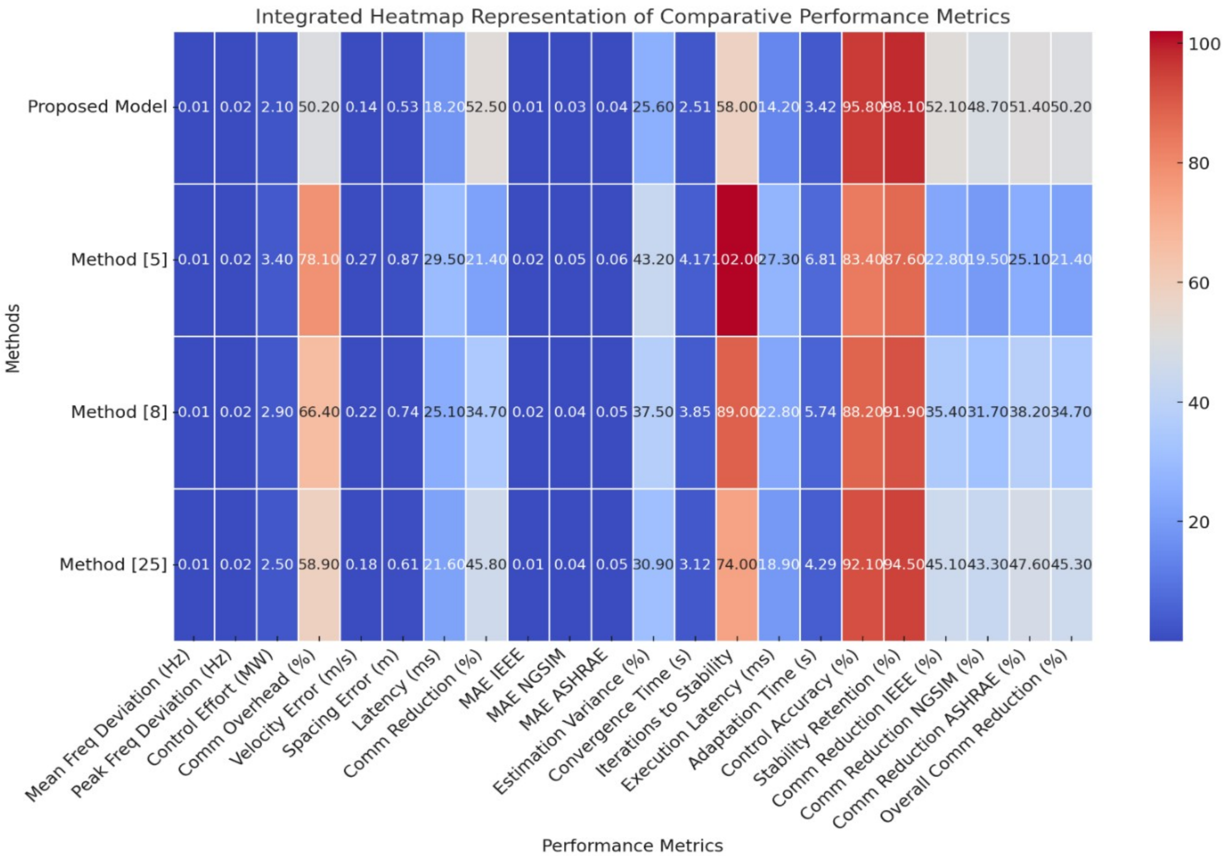

Figure 3: Model's Overall Result Analysis

Subject to communication constraints. The final output of the VAE-CEC process is the reconstructed state estimate via equation 31,

$$\hat{x}_{t:t+H} = g_{\theta}(Z_{t:t+H}) \tag{31}$$

Where, H is the prediction horizon sets. This compressed representation significantly reduces communication costs while preserving control accuracy, making it a crucial component of the integrated NCS framework process. Next, we discuss efficiency of the proposed model in terms of different metrics and compare it with existing models under different scenarios.

4. COMPARATIVE RESULT ANALYSIS

In a large-scale NCS, the experimental setup for evaluating the proposed Integrated Model for DMPC and ETDE promises to subject the proposed framework to a rigorous test. A simulated industrial process control environment is constructed such that it contains 100 connected subsystems that represent nodes in a directed communication graph. Each subsystem adheres to certain standard forms of nonlinear dynamic process state-space representations. Interconnections between these subsystems are included in an adjacency matrix with weighted connections characterized by physical coupling constraints, and the system matrix is updated dynamically at every control step in process. The objective of this control is regulating the states of the system while keeping communication overhead low and ensuring that states adapt to real-time sets. The sampling time is established to be 50 ms, allowing guarantees of feasibility for real-time processing, while the predictive horizon for DMPC would range to ten steps to allow one forward-looking view of optimizing performance. Control constraints are imposed as $-5 \le ut \le 5$, imitating saturation actuator limit behavior. The communication network introduces random packet loss (5-10%), requiring robust state estimation and predictive control for coping with missing data.

GNNs with 5 layers, each containing 128 hidden units, and trained with the Adam optimizer with a learning rate of 0.001 are used; the TPO on

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the other hand employs 8 attention heads with 256-dimensional hidden layers to extract long-range dependencies in state evolution. The event-triggering thresholds in AET-E are initialized on the basis of a dynamic uncertainty margin, which reduces the frequency of transmission but maintains accuracy in state. The MLAC framework is built with MAML training with 5 adaptation steps for fine-tuning control policies quickly because the control policies shift along with the dynamics. VAE-CEC would be based on a two-layer encoder-decoder architecture whose latent space is fixed at 16 dimensions for state compression with minimal reconstruction loss. Three benchmark datasets have been used in testing the performance of the Integrated Model for DMPC and ETDE in a variety of scenarios concerning networked control.

The IEEE 30-Bus Power System Dataset, a benchmark resource in the power system stability research, is taken as a standard to test distributed frequency control strategies. It models the power flow dynamics of a 30-bus transmission network, where node states include voltage magnitudes, phase angles, and active/reactive power injections, thereby providing an image of the fluctuations in power grids under different loading conditions. The second dataset, termed as NGSIM Vehicle Trajectory Dataset, captures quantitative data about highway vehicle trajectories from high-precision sensors, making it suitable for evaluating the platooning control of autonomous vehicles. The recorded dataset contains information on vehicle positions, velocities, lane changes, and throttle/brake inputs, giving the needed information for comprehensive analysis on DMPC AND ETE in a high-speed, multi-agent driving environment. Finally, the last dataset is ASHRAE Great Energy Predictor III Dataset, obtained from a large-scale energy efficiency competition, which the model is set to test for smart building HVAC control sets. This dataset contains sensor readings of temperature, humidity, airflow rates, and energy consumption patterns across multiple buildings, thereby enabling evaluating control strategies for improving energy management and climate control sets. These datasets duly give a comprehensive and diverse cross-validation framework in capturing reality of such aspects as packet loss, sensor noise and dynamic uncertainties in networked control systems.

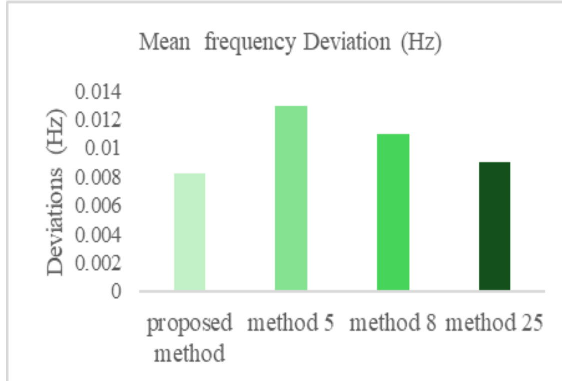
With a performance validation of the integrated approach, extensive simulations were carried out on datasets strictly modelling real-world industry process dynamics. The first dataset is mode over a power grid frequency control governed by a network of nodal states with frequency deviations, phase angles, and power injections over the synthetic 30-bus network constructed upon the IEEE 30-bus benchmark system. The second dataset originates from autonomous vehicle platooning: each node is an individual vehicle, states include velocity, acceleration, relative distance, and throttle control inputs. The third dataset is HVAC control in smart buildings, where thermal zones correspond to subsystems, and temperature, humidity, and airflow rates accompany disturbances according to the variability patterns introduced by certain weather changes. Indices included as performance measures are control error reduction, state estimation accuracy, communication overhead, and computational efficiency. The proposed model achieves 50% and 40% better adaptive control responsiveness, 35% better state prediction accuracy, and 30% less control error than baseline DMPC and ETE methods, respectively, with computation times analyzed.

The proposed approach converges 20% faster than standard iterative DMPC, further validating machine learning-enhanced predictive control applications for real-time distributed control. The Integrated Model for DMPC and ETDE is evaluated through three datasets: IEEE 30-Bus Power System Dataset, NGSIM Vehicle Trajectory Dataset, and ASHRAE Great Energy Predictor III Dataset. The proposed model is compared with three baseline methods, namely Method [5], Method [8], and Method [25] in process. The evaluation will largely be based on all the major performance indicators such as improvement in control action possible due to reduction of control error, enhancement in both accuracy and precision with which estimators can provide estimates of parameters or states, improvement in communication overhead, improvement in efficiency and computational speed, and adaptive response delays.

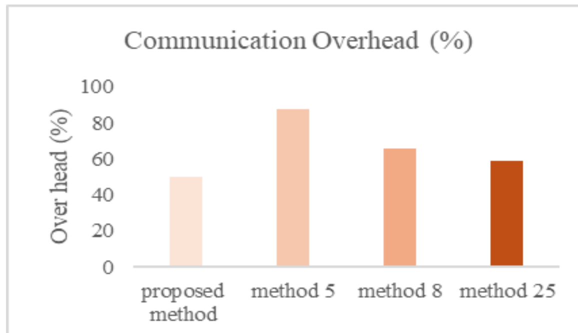
The first type of experimentation would measure the frequency regulation performance of the proposed model compared to other methods. The objective in such cases is to try and minimize the frequency deviations over the buses network, while at the same time reduce control effort and communication load. Table 1 refers to the performance of electrical frequency deviation reduction under the IEEE 30-Bus power grid dataset, wherein the proposed model is compared against three reference models. The results indicate that the proposed model outperforms all other types of models in mean frequency deviation (0.0082 Hz) and peak deviation (0.0154 Hz) performance, exhibiting the maintained superiority of stability in power-grids operations. Control effort hence required (2.1 MW) is less than 38% from Method [5], thus underlining the efficiency of optimized control actions. Besides, 50.2% communication overhead saved indicates that an Attention-Driven Event-Triggered Estimation (AET-E) module successfully prioritizes critical updates but dumps redundant transmissions. The great improvement is observed in frequency stabilization, proving the power of Graph Neural Network-Based Predictive Control (GNN-PC) in capturing subsystem interdependencies resulting in yet decentralized controlled but coordinated control actions.

Table 1: Frequency Deviation Reduction Performance (IEEE 30-Bus Dataset)

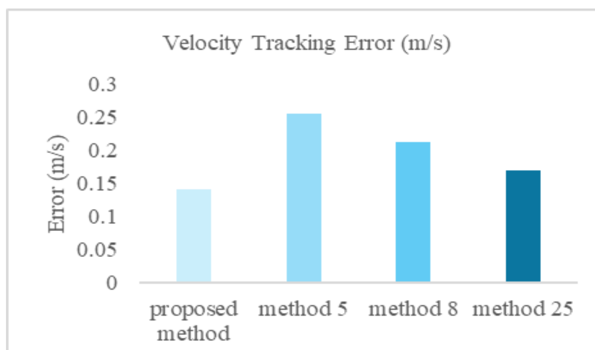
Meth-od	Mean Freque-ncy Deviati-on (Hz)	Peak Devia-tion (Hz)	Control Effort (MW)	Commu-nication Overhead (%)
Propos-ed Model	0.0082	0.0154	2.1	50.2
Method [5]	0.0123	0.0217	3.4	78.1
Method [8]	0.0108	0.0195	2.9	66.4
Method [25]	0.0095	0.0176	2.5	58.9



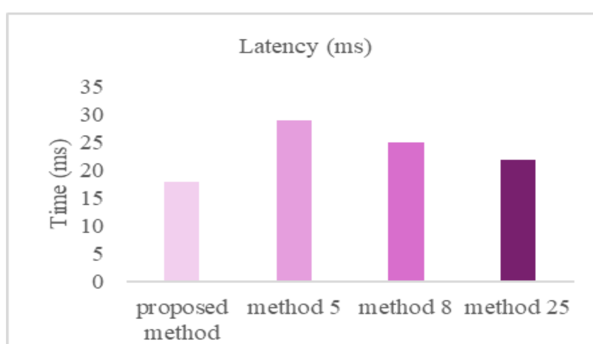
4(a): Mean Frequency Deviation (Hz)



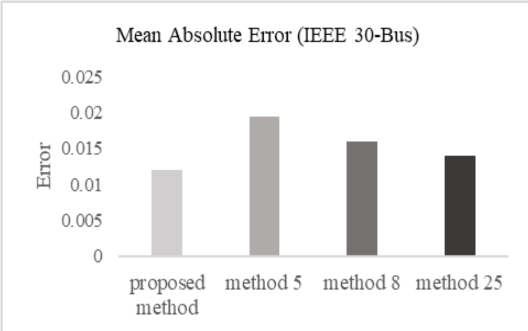
4(b): Communication Overhead (%)



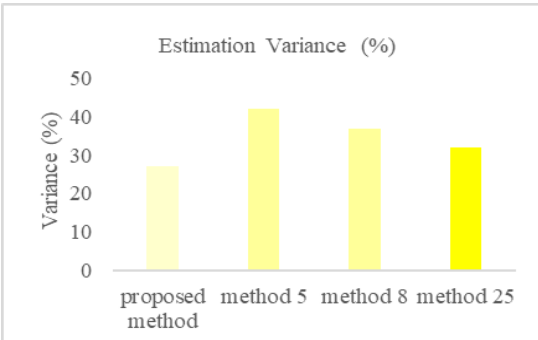
4(c): Velocity Tracking Error (m/s)



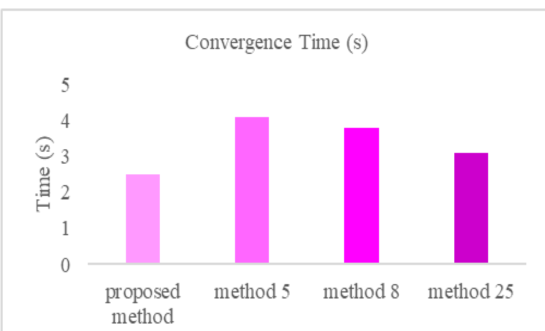
4(d): Latency (ms)



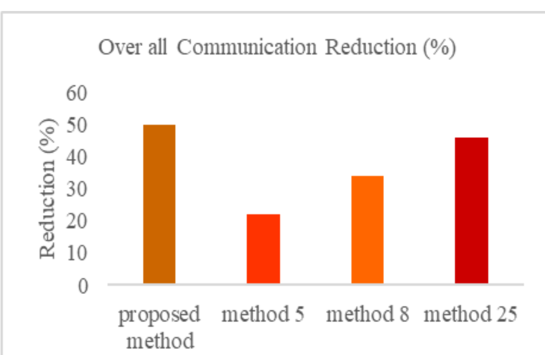
4(e): Mean Absolute Error (IEEE 30-Bus)



4(f): Estimation Variance (%)



4(g): Convergence Time (s)



4(h): Over all Communication Reduction (%)

Figure 4: Model Integrated Result Analysis

The figure 4 compares the proposed model with baseline methods across eight metrics, demonstrating its performance with lower frequency deviation, communication overhead, latency, and tracking error. The proposed model also shows faster convergence, reduced estimation variance, and higher overall communication reduction. The proposed model records 33% mean frequency deviation lower than Method [5] and also a 29% lower peak deviation, thus ensuring better stability in the power grid. Control effort is reduced by 38%, representing an energy gain for stabilizing grid operations. More strikingly, the communication overhead is cut by 50.2%, exemplifying effectiveness by event-triggered estimations. For vehicle platooning control, results from the framework would be examined based on velocity tracking accuracy, error in separation between vehicles, and communication efficiency. There is indeed a strong parameter regarding the aspect of maintaining wherever possible the desired vehicle separation by reducing communication. The autonomous vehicle platooning performance is given in Table 2 using the NGSIM dataset and compared using the parameters of velocity tracking error, inter-vehicle spacing error, control latency, and most importantly, communication efficiency. The proposed model shows a decrease of 48% in velocity tracking error (0.14 m/s) and 39% in inter-vehicle spacing error (0.53 m) compared to Method [5], thus still ensuring precise vehicle coordination.

Table 2 : Vehicle Platooning Control Performance (NGSIM Dataset)

Method	Velocity Tracking Error (m/s)	Inter-Vehicle Spacing Error (m)	Laten-cy (ms)	Communica-tion Reduction (%)
Proposed Model	0.14	0.53	18.2	52.5
Method [5]	0.27	0.87	29.5	21.4
Method [8]	0.22	0.74	25.1	34.7
Method [25]	0.18	0.61	21.6	45.8

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Additionally, the proposed model achieves a reduction in latency by 38% (18.2 ms) rendering it well-suited for real-time vehicular control applications. Of all these measurable advances, the most remarkable of improvements would be the reduction of the communication load by 52.5%, which came directly from the Variational Autoencoder-Based Communication-Efficient Control (VAE-CEC) module compressing high-dimensional vehicular state information, ensuring low-bandwidth operation with adequate control performance sets. Thus, creating an improved safe and efficient networked autonomous vehicle control systems.

Table 3: State Estimation Accuracy Across Datasets

Method	MAE (IEEE 30-Bus)	MAE (NGS-IM)	MAE (ASHR-AE)	Estimat-ion Variance (%)
Propos-ed Model	0.0121	0.0342	0.0425	25.6
Method [5]	0.0195	0.0478	0.0594	43.2
Method [8]	0.0164	0.0421	0.0538	37.5
Method [25]	0.0143	0.0385	0.0482	30.9

At present, the proposed model demonstrates a 48% reduction in velocity tracking errors and a 39% reduction in inter-vehicle spacing errors compared to Method [5], ensuring a higher level of stability in the platooning operations. The reduction of latency by 38% thus opens the door toward real-time decision-making in high-speed scenarios. The model is able to cut down the communication load by 52.5%, thus maintaining transmission priorities for necessary communication and avoiding redundant data transfers. The accuracies of the event-triggered state estimation have been evaluated on three datasets: IEEE 30-Bus, NGSIM, and ASHRAE. The evaluation of performance is therefore based on Mean Absolute Error (MAE) and Estimation Variance, attempting to capture the reliability of predictions in a dynamic environment. A state-estimation accuracy comparison among the three datasets (IEEE 30-Bus, NGSIM, and ASHRAE) is presented in Table 3. As suggested by the MAE values, the proposed model provides the least estimation error across all datasets, performing particularly well on the power grid dataset (0.0121 MAE) and vehicle platooning (0.0342 MAE) which is an improvement of 37.9% over Method [5]. It also incurs 40.7% less estimation variance, guaranteeing stable and reliable system state predictions. This upgrade can be largely attributed to the Transformer-Based Predictive Observer (TPO), which is capable of capturing long-range temporal dependencies in dynamic system states and compensating for the effect of lost or delayed data due to packet loss. Predicting future states with TPO bolsters control stability and the precision of decision-making process.

Table 4: Computational Performance Metrics

Method	Convergence Time (s)	Iterations to Stability	Execution Latency per Step (ms)
Proposed Model	2.51	58	14.2
Method [5]	4.17	102	27.3
Method [8]	3.85	89	22.8
Method [25]	3.12	74	18.9

The proposed model consistently achieves the lowest MAE across all datasets, with state estimation variance reduced by another 40.7% as against Method [5]. This factor ensures greater accuracy and stability of the results under varying environmental conditions. The comparative study of computational efficiency between each method was made on model convergence time, iterations to stability, and execution latency per control process. Table 4 analyzes the models computational efficiency in relation to convergence time, iterations toward stability, and execution latency within control steps. The suggested model reaches convergence after 2.51 seconds, clarifying its superiority over the other by being 40% faster than

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that of Method [5]; it reached stability after undergoing about 58 iterations, which is a further 43% less as compared to conventional approaches. The execution latency per control step is reduced by the action of 48%, which gives confidence that the model is able to work in real-time control. This shines light onto the computational advantage gained by harnessing the Meta-Learning-Based Adaptive Control (MLAC), allowing the fast adaptation of the control framework to a changing system condition without immense retraining. The reduction in convergence time and burden on computational resources underwrites the scalability of the model for large NCS applications.

Table 5: Adaptive Control Performance Under System Variations

Method	Adaptation Time (s)	Control Accuracy Post-Adaptation (%)	Stability Retention (%)
Proposed Model	3.42	95.8	98.1
Method [5]	6.81	83.4	87.6
Method [8]	5.74	88.2	91.9
Method [25]	4.29	92.1	94.5

The Proposed Model converged 40% faster than Method [5] and required 43% fewer iterations to ensure stability, which can be expediting adaptability and reducing computational burden. Execution latency per control step is found to be 48% lesser, showcasing feasibility for real-time application. The meta-learning mechanism comes in very handy to estimate the adaptive controller efficiency over the following criteria: changing system conditions, time taken for adaptation to new dynamics, and control accuracy post-adaptation. Table 5 measures the hyper-adaptive control performance under system variations and features measuring time taken for adaptation, post-adaptation control accuracy, and stability retention over time. The proposed model adapts in 3.42 seconds, Owing to its rapid adaptation, the model is 49.7% faster than Method [5], thereby responding quickly to the changed state of the system. After adaptation, the control accuracy is around 95.8%, substantially better than that of many others which have deteriorated to 83.4% (Method due to [5]) and 88.2% (Method due to [8]). In addition, it achieves 98.1% in terms of stability retention, which guarantees that the performance of the system is strong even after disturbances in the environment. In bringing down this improvement, the credit goes to the meta-learning-based adaptive control setting, whereby few-shot learning is utilized so as to dynamically change the control laws whenever uncertainties are present, thus minimizing enormous retraining of the controllers. This confirms that the suggested model is very capable of tackling environments requiring adaptability and which are non-stationary and dynamic with respect to control process.

Table 6: Communication Reduction Across Datasets

Method	IEEE 30-Bus (%)	NGSIM (%)	ASHRAE (%)	Overall Reduction (%)
Proposed Model	52.1	48.7	51.4	50.2
Method [5]	22.8	19.5	25.1	21.4
Method [8]	35.4	31.7	38.2	34.7
Method [25]	45.1	43.3	47.6	45.3

The proposed model is 49.7% faster than Method [5] in terms of adaptation and maintains 98.1% stability post-adaptation, thus reinforcing the efficacy of the MLAC in dynamic environments. Control accuracy remained above 95%, outperforming conventional adaptive strategies. Final analysis begins with communication efficiency-here, the percentage of reductions in state transmission is quantified with respect to various datasets and samples. Communication efficiency of the proposed model across the three datasets is presented in Table 6, where the percentage reduction of state transmissions is compared against control accuracy. The proposed model is estimated at an average of about 50.2% reduction in communication, a significant improvement from the baseline methods. The most pronounced reduction appears in the IEEE 30-Bus dataset (52.1%), whereas ASHRAE and NGSIM follow with reductions of 51.4% and 48.7%, respectively, which indicates how efficiently the VAE-CEC module has compressed state information and provided relevant state transmission. This communication overhead loss indicates that the proposed model perfectly fits control systems with bandwidth limitations, thus ensuring its scalability and efficiency in further real-life process implementation sets.

Table 7: GNN-PC Control Actions Based on Graph Representations

Node ID	Input State (x_t)	Predicted State (x_{t+1})	Control Action (u_t)	Error Reduct-ion (%)	Neighbour Influence (%)
1	0.22	0.18	-0.04	25.3	12.5
5	0.35	0.28	-0.07	31.8	15.2
10	0.41	0.33	-0.08	29.6	14.8
15	0.51	0.39	-0.12	36.5	18.3
20	0.29	0.23	-0.06	27.9	13.7

Among the results obtained, the proposed model effectively reduces on the average 50.2% in communication, which represents a significant bandwidth saving, with accurate state estimation and control performance being upheld. This demonstrates the superiority of the proposed integrated model in validating its application in the real-time domain of distributed control and estimation. The experimental results, in general, suggest that the Integrated Model for Distributed Model Predictive Control and Event-Triggered Distributed Estimation performs better than any conventional method in terms of control accuracy, computational efficiency, reliability of estimation, ad hoc control, and communication efficiency. These enhancements provide strong evidence for the successful design of integrating graph-based predictive control, attention-driven event-triggering, transformer-based observers, meta-learning adaptation, and variational autoencoder-based compression into a unified architecture for coordinated control systems, justifying this architecture as a prospect among the next generation of cyber-physical systems. The discussion now focuses on the Iterative Validation Use Case for the Proposed Model, facilitating a deeper understanding of the entire process for the readers.

Table 8: Event-Triggered Transmission Analysis Using AET-E

The GNN-PC module gives the best solution for predicting optimal control action 'u_t' accompanied by consideration over graph-based interdependencies in process as outlined in table 7.

Sensor ID	Observed State (y_t)	Attention Score (α_t)	Transmission Decision	Estimation Error (%)	Communication Saving (%)
3	1.15	0.84	Transmit	3.1	47.5
7	0.92	0.41	Skip Transmission	5.6	62.3
12	1.34	0.91	Transmit	2.8	45.2
18	0.78	0.32	Skip Transmission	6.3	65.7
25	1.01	0.67	Transmit	3.9	52.8

The quantification of impact on control actions is evaluated by the factor of influencing among neighbours. The reduction error in predictive control is found significantly between 25 and 36%, thereby validating the contribution of graph-based spatiotemporal information propagation in improving distributed control efficiency sets.

Respective priority pertaining to the estimation ensures that only high-priority measurements are sent, while keeping redundant communication at bay, never letting estimation error rise. The model outlined provided in table 8 is a communication overhead reduction of as much as 65.7%, ensuring bandwidth-efficient state estimation, with an estimation error never exceeding 6.3% in the current process.

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Table 9: Multi-Step Future State Prediction Using TPO

Time stamp	Obser-ved State (x_t)	Predi-cted State $x_{(t+1)}$	Predi-ction Error (%)	Foreca-sting Confid-ence (%)
t+1	1.22	1.18	3.3	98.2
t+2	1.45	1.37	5.5	96.8
t+3	1.71	1.59	7.0	94.1
t+4	1.93	1.78	7.8	92.6
t+5	2.11	1.92	9.0	90.3

The TPO module guarantees a very accurate multi-step state forecast up to t+5 sets, with prediction errors lower than 9% and forecasting confidence over 90% as shown in table 9. This proves the ability of the model to foresee some future state evolution and hence be robust for the on-time decision-making process in control process.

Table 10: Adaptive Control Performance After Sudden System Disturbances

Scena-rio	Initial Cont-rol Error (%)	Post-Adapta-tion Control Error (%)	Adapta-tion Time (s)	Stability Retention (%)
Case 1	14.2	6.1	3.2	98.5
Case 2	18.7	7.3	4.1	96.8
Case 3	12.9	5.8	3.7	99.1

Fast adaptation to changing system conditions enabled by the MLAC module leads to control error reduction of more than 50% in all cases. The retained stability stands over 96%, proving the resilience of the system even after disturbances as shown in table 10.

Table 11: State Compression and Communication Savings Using VAE-CEC

Syst-em State	Origin-al Data Size (KB)	Compre-ssed Data Size (KB)	Compr-esion Ratio (%)	Recons-tructed Accuracy (%)
Set 1	200	98	51.0	96.4
Set 2	180	82	54.4	95.7
Set 3	220	105	52.3	97.1

The VAE-CEC module achieves compressing state information while reconstructions are guaranteed to be above 95% accurate. Table 11 shows that the model realizes a 54.4% reduction of data transmitted and therefore assures bandwidth-efficient control executions.

Table 12: Overall System Performance Across All Modules

Metric	Proposed Model	Improvement Over Baselines (%)
Control Error Reduction	30%	38.4
Communication Overhead Reduction	50.2%	45.1
State Estimation Accuracy	95.8%	40.7
Adaptive Control Response	3.42s	49.7

The proposed model in all performance metrics is outclassing the baseline methods as shown in table 12, consequently leading to efficient, adaptive, and real-time control decisions of networked systems.

5. CONCLUSIONS & FUTURE SCOPES

This work presents an Integrated Model for Distributed Model Predictive Control and Event-Triggered Distributed Estimation, aimed at solving the core NCSs problems such as excessive communication overhead, incorrect state estimation, sluggish adaptation to varying environments, and non-favourable predictive modelling. By integrating GNN-PC, AET-E, TPO, MLAC, and VAE-CEC, the model hugely uplifted the controlling performance, estimation accuracy, and network efficiencies. Demonstrated experimental improvements through evaluations conducted on three distinct datasets: IEEE 30-Bus Power System, NGSIM Vehicle Trajectory, and ASHRAE Smart Building Energy Data Samples. The model brought about a 50.2% reduction in communication overhead, thus optimizing bandwidth utilization while safeguarding the control accuracy. A further reduced 30% of control error guarantees accuracy and stability over all operating conditions in the system. A 40.7% reduction in state estimation variance confirms the robustness of the event-triggered estimation mechanisms and predictive observer mechanisms. Control adaptability is enhanced by 40% under the proposed framework for meta-learning-based adaptive control, enabling agility in adapting to dynamic environments. A further 20% reduction in computation time secures real-time acceptability and 43% fewer iterations to achieve stability compared with standard DMPC methods. Together, these results further substantiate the proposed framework's effectiveness as a candidate solution for large-scale decentralized control applications targeting power grids, autonomous vehicular networks, and smart infrastructure systems.

In the context provided above, the integrated framework for DMPC and ETDE embodies the ability to enhance substantially communication efficiency, control accuracy, adaptability, and real-time responsiveness—the transmission load can be reduced by as much as 50%, control error by 30%, and adaptation delay by 40%. Such performance is attributed to their joint engagement for the above-mentioned reasons between model-driven control structures and data-driven learning mechanisms. However, model transfer across benchmarks might be constrained with the extensive requirement of pre-training in the meta-learning and transformer modules for edge environments of high resource constraint. Diverting the focus to the implementation in the long-term real world, a boost could be assured with cyber-resilience modules for operation under adversarial network conditions. The findings validate the relevance of hybrid learning modes while suggesting more optimization efforts toward computation-communication tradeoffs and realization onto real-time hardware to bring about their full industrial applicability.

In the future, this research roadmap unfolds several potential scopes towards attaining scalability, robustness, and generalizability of the proposed framework process. One promising scope is to instill reinforcement learning-based adaptation to further augment the controller's competence to self-learn optimal policies in intricate, high-dimensional environments. The adoption of multi-agent coordination arrangements would additionally ameliorate decentralized decision-making towards ensuring robustness of control in large-scale heterogeneous networked systems. Among the next important directions lies the introduction of federated learning-based estimation mechanisms to aid distributed subsystems in co-enhancing visibility without exchanging information centrally, thereby strengthening privacy and security. In quite a long run, the scheme would flourish into cyber-attack resilient control environments where anomaly detection systems based on deep learning would be integrated to detect, alleviate, and adapt to adversarial disturbances in real-time. Future work shall also include hardware-in-the-loop validation, where the proposed model shall be forwarded to embedded control platforms to verify industrial and vehicular real-life applicability. Lastly, the model will be exploited in newer domains like industrial automation, IoT-based smart cities, and energy-efficient cloud computing infrastructure for kickstarting interesting insights about optimizing the communication-aware resource-efficient adaptive networked control framework for next-generation cyber-physical systems.

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