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Future Smart Cities As Cyber-Physical Systems: Economic Challenges and Opportunities

Elahe Taherianfard, Mohammad Hossein Heydari, Taher Niknam, Aliasghar Baziar, Mohammadreza Askari

***Abstract*—This study explores the integration of Variational Autoencoders (VAEs) and Genetic Programming (GP) to address key challenges in the development of smart cities as cyber-physical systems (CPS). The primary objective is to enhance decision-making processes, optimize resource allocation, and improve energy management within urban infrastructures. VAEs are employed for dimensionality reduction and feature extraction, enabling efficient processing of large-scale urban data, while GP is utilized for optimization, ensuring the effective configuration and management of smart city systems. The proposed framework is evaluated across various metrics, including energy consumption, system resilience, and traffic flow optimization. The results demonstrate substantial improvements over traditional methods, highlighting the potential of the VAEs + GP combination in tackling complex CPS challenges. This approach not only contributes to the advancement of smart city technologies but also offers a scalable and adaptive solution to the evolving demands of urban environments. Overall, the study showcases the transformative potential of combining deep learning and evolutionary algorithms to build sustainable and intelligent smart cities.**

***Index Terms*—Smart Cities, Cyber-Physical Systems (CPS), Variational Autoencoders (VAEs), Genetic Programming (GP), Resource Allocation, Energy Management, Dimensionality Reduction, Optimization Algorithms, Urban Data Processing, Intelligent Systems**

I. Introduction

THIS era of rapid urbanization and technological evolution has led to the emergence of the concept of "smart cities," where cities leverage advanced technologies to enhance urban living, ensure sustainability, and optimize resource management. Smart cities rely on the seamless integration of physical infrastructure with digital systems, creating what is known as cyber-physical systems (CPS) [1]. These systems are a sophisticated amalgamation of computing, communication, and control technologies that interact with physical processes to enable real-time decision-making and optimization. The synergy between smart cities and CPS represents a paradigm shift in urban development, addressing the challenges of growing populations, resource constraints, and the demand for improved quality of life [2]. The evolution of smart cities and CPS technologies has been marked by significant milestones. In the early phases, the emphasis was primarily on the deployment of sensors and networks to monitor and manage urban infrastructure. Over time, the integration of advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and edge computing has transformed the landscape [3], [4], [5]. CPS now enables not only data collection but also real-time processing, predictive analytics, and automated responses [6]. For instance, smart transportation systems equipped with CPS can reduce traffic congestion and enhance safety through dynamic traffic management, while smart energy grids optimize power distribution and integrate renewable energy sources [7]. One of the key drivers behind the adoption of CPS in smart cities is its ability to address complex urban challenges. Traditional city management approaches often struggle with issues such as inefficient resource allocation, environmental degradation, and limited scalability [8]. CPS provides a solution by offering real-time situational awareness and adaptive capabilities. By integrating diverse data sources, CPS can model and predict urban dynamics, enabling proactive measures to mitigate issues [9]. For example, smart water management systems powered by CPS can detect leaks, forecast demand, and ensure equitable distribution, contributing to sustainable urban growth. The importance of CPS in addressing urban challenges extends beyond infrastructure optimization [10]. CPS plays a crucial role in enhancing public safety, healthcare, and governance. In public safety, CPS-powered surveillance systems can detect anomalies and alert authorities to potential threats, ensuring timely intervention [11]. In healthcare, CPS applications such as wearable health monitors enable real-time tracking of patient conditions, reducing hospital visits and improving patient outcomes. Governance systems integrated with CPS can facilitate data-driven policy-making, enhancing transparency and accountability [11]. Despite the promising potential of CPS, its implementation in smart cities is not without challenges [12]. These include technological constraints such as interoperability and scalability, as well as concerns over data privacy and cybersecurity [13]. The social and ethical implications of CPS adoption, including issues of inclusivity and equitable access, must be carefully addressed. Understanding these challenges and proposing innovative solutions is vital for the successful realization of smart cities as sustainable and inclusive urban ecosystems.

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Existing approaches in smart cities and Cyber-Physical Systems (CPS) face significant limitations despite advancements in areas like transportation, IoT security, and sustainability [14]. Cyber vulnerabilities, scalability issues, and high computational overheads hinder frameworks like blockchain and game theory. Integration challenges, such as ambiguous definitions in Cyber-Physical-Social Systems (CPSS) and socio-technical constraints in participatory planning, limit their practical deployment [15]. Digital Twins and data-driven engineering, while promising for real-time insights, grapple with privacy concerns, synchronization challenges, and resource constraints [16]. Pundir et al. (2022) explored CPS-enabled transportation networks, highlighting the synergy of smart sensors and intelligent controls in enhancing mobility infrastructure while addressing cyber vulnerabilities [16]. Khalil et al. (2022) underscored the role of blockchain in authenticating IoT devices within smart cities, proposing lightweight solutions to mitigate computational overheads and ensure secure operations [17]. Pasandideh et al. (2022) introduced a taxonomy for Cyber-Physical-Social Systems (CPSS), integrating social dynamics into CPS frameworks to enhance system interoperability and functionality [18]. Kuru and Ansell (2020) proposed the TCitySmartF framework, emphasizing socio-technical transitions for citizen- and resource-centric smart city transformation [19]. Jafari et al. (2023) discussed Digital Twin (DT) technology for real-time data management in transportation and power grids, tackling multidimensional challenges in urban energy systems [20]. Zhang et al. (2023) highlighted advancements in Industrial CPS (ICPS), focusing on architecture and stakeholder collaboration for industrial applications [21]. Lastly, Broo and Schooling (2021) emphasized using data as an engineering tool to optimize smart infrastructure design and lifecycle management. These shortcomings underscore the need for scalable, secure, and efficient frameworks that address the complexity and heterogeneity of CPS-enabled smart environments.

This article aims to explore the challenges and opportunities associated with smart cities as cyber-physical systems. It focuses on the technological, social, and environmental barriers to CPS implementation and proposes a robust framework leveraging Variational Autoencoders (VAEs) and Genetic Programming (GP) [22]. The article also highlights the transformative potential of this combination, emphasizing its capacity to optimize urban systems and address the multifaceted challenges of smart city development. The scope of this article is broad, encompassing both the technical and non-technical dimensions of CPS in smart cities [23]. It seeks to provide a comprehensive understanding of the evolving landscape, from the foundational technologies driving CPS to the emerging trends and future directions [24]. By integrating case studies and real-world applications, the article demonstrates the practical implications of CPS in urban contexts. Additionally, it underscores the role of policymakers, urban planners, and stakeholders in fostering a collaborative approach to CPS deployment [25]. This article positions itself as a valuable resource for researchers, practitioners, and policymakers interested in the intersection of CPS and smart cities. By addressing the challenges and proposing innovative solutions, it contributes to the ongoing discourse on sustainable urban development [26]. The subsequent sections will provide an in-depth analysis of the key challenges, a detailed discussion of the proposed methodology, and insights into the opportunities and future directions for smart cities as cyber-physical systems.

II. Key Challenges

The implementation of cyber-physical systems (CPS) in smart cities faces significant challenges across technological, cybersecurity, social, ethical, and environmental domains. Technologically, scalability, interoperability, and real-time data integration are key issues [27]. Systems must handle increasing urban demands efficiently, ensure seamless communication across diverse platforms, and process vast amounts of data in real time without delays. Cybersecurity threats, such as unauthorized access and ransomware, pose substantial risks, requiring robust encryption, intrusion detection, and secure communication systems while balancing performance and security [28]. Social and ethical concerns include safeguarding citizen privacy, ensuring equitable access, and preventing social inequalities. Environmentally, CPS must address energy consumption, electronic waste, and carbon footprints by integrating renewable energy and optimizing resource usage [29]. To tackle these challenges, a structured approach is proposed, focusing on optimizing scalability, interoperability, data integration, cybersecurity, privacy, inclusivity, and sustainability. This approach uses constraints and an objective function to balance system performance, resource efficiency, and social equity, ensuring CPS can scale effectively without overloading as urban infrastructure expands.

$$\int_0^T \left(\sum_{i=1}^{N} x_i(t) \right) dt \leq S_{\text{max}} \cdot \log \left(1 + \sum_{i=1}^{N} x_i^2 \right) \tag{1}$$

Where $x_i(t)$ represents the state of each device at time t, and the logarithmic term models the diminishing returns as more devices are added, scaling with x_i^2. Interoperability requires low communication latency between devices, allowing seamless data exchange. This constraint takes into account not only the latency between devices but also the signal degradation between them, using a non-linear model that captures complex communication dynamics.

$$\max_{i,j} \left(\frac{d_{ij}}{1+\alpha_{ij}} \right) \leq \Delta_{\text{max}} \cdot \left(\prod_{i=1}^{N} \left(\sin \left(\frac{d_{ij}}{\beta} \right) \right) \right) \tag{2}$$

Where d_{ij} is the latency between devices i and j, and α_{ij} is an attenuation factor based on the signal quality. The sine term models the non-linear effects of signal degradation. The real-time integration of data is crucial for maintaining system responsiveness. This constraint ensures that data processing times do not exceed a defined limit, incorporating an exponential decay to model the diminishing returns as time increases, which ensures rapid processing within acceptable thresholds.

$$\begin{aligned} &\int_0^T \left(\sum_{i=1}^{M} \left(t_i \cdot \exp \left(-\frac{t_i}{T_{\text{max}}} \right) \right) \right) dt \\ &\qquad \leq T_{\text{max}} \cdot \ln \left(1 + \sum_{i=1}^{M} t_i^2 \right) \end{aligned} \tag{3}$$

Where t_i is the processing time for each data packet. The exponential term ensures that the system prioritizes lower processing times, with diminishing returns as time increases. Protecting data integrity from cyber threats is paramount.

This constraint addresses the probability of data breaches over time, incorporating a correction factor for network resilience and ensuring that the likelihood of a successful compromise remains within tolerable limits.

$$\int_0^T P_{\text{c}}(t)\, dt \leq \epsilon_{\text{max}} \cdot \left(1 - \prod_{i=1}^{N} \left(1 - \frac{P_i}{\gamma}\right)\right) \tag{4}$$

Where $P_{\text{c}}(t)$ is the probability of data breach over time, and P_i represents the breach probability at device i, with a correction factor γ for network resilience. In order to maintain sustainability, energy consumption must be optimized. This constraint accounts for the energy consumption of each device and includes an exponential decay model that ensures energy use decreases over time while maintaining system efficiency.

$$\sum_{i=1}^{N} \left(E_i \cdot \left(1 + \alpha_i^2\right)\right) \leq E_{\text{max}} \cdot \left(\int_0^T \exp\left(-\frac{t}{\tau}\right) dt\right) \tag{5}$$

Where E_i is the energy consumption of each device and α_i represents energy efficiency, with an exponential decay in system energy use over time modeled by the integral. The privacy of users and their data must be safeguarded in smart city environments. This constraint ensures that the proportion of anonymized data is sufficiently high to meet privacy requirements, using a logarithmic function to capture the cumulative impact of anonymization efforts across the system.

$$\frac{\int_0^T D_{\text{a}}(t)\, dt}{\sum_{i=1}^{N} x_i} \geq \alpha_{\text{min}} \cdot \ln\left(1 + \prod_{i=1}^{N} D_i\right) \tag{6}$$

Where $D_{\text{a}}(t)$ is the proportion of anonymized data over time, and D_i represents anonymization efforts for each device. The logarithmic product represents the cumulative effect of anonymization. Inclusivity ensures that all users and communities in the smart city have equal access to resources and services. This constraint models the accessibility of each user and incorporates a non-linear function to emphasize the importance of ensuring equitable distribution across all groups.

$$\frac{1}{N} \sum_{i=1}^{N} a_i \cdot \exp\left(-\frac{a_i}{\beta}\right) \geq \beta_{\text{min}} \cdot \prod_{i=1}^{N} \left(1 - \frac{a_i}{\gamma}\right) \tag{7}$$

Where a_i represents the accessibility index for the i-th user or community. The exponential term emphasizes the nonlinear impact of access, while the product term ensures equitable distribution. Sustainability is critical for ensuring the long-term viability of smart city infrastructures. This constraint limits the carbon footprint of the system, capturing diminishing returns with a logarithmic model that penalizes excessive emissions.

$$\sum_{i=1}^{N} \left(C_i \cdot \left(1 + \frac{\ln(C_i)}{\beta}\right)\right) \leq C_{\text{max}} \cdot \int_0^T \frac{e^{\delta t}}{1 + e^{\delta t}} dt \tag{8}$$

Where C_i is the carbon footprint of each device, and the logarithmic term captures diminishing returns in carbon emissions. The integral ensures that carbon output stays within allowable limits over time. Resource usage in a smart city must be carefully managed to ensure efficiency. This constraint models the total resource consumption, accounting for diminishing returns and ensuring that the system uses resources efficiently without exceeding predefined limits.

$$\sum_{i=1}^{N} r_i \cdot \left(1 + \frac{r_i^2}{R_{\text{max}}}\right) \leq R_{\text{max}} \cdot \left(\prod_{i=1}^{N} \left(\frac{1}{1 + r_i}\right)\right) \tag{9}$$

Where r_i is the resource usage of the i-th component (e.g., power, water), and R_{max} is the maximum allowable resource usage. The product term captures diminishing returns as resource use increases. To ensure the reliability of the system, fault tolerance is key. This constraint ensures that the number of system failures remains within a specified threshold, incorporating a product term that models the fault tolerance at each device level.

$$F_{\text{max}} \leq \theta_{\text{max}} \cdot \left(1 - \prod_{i=1}^{N} \left(1 - \frac{F_i}{\lambda}\right)\right) \tag{10}$$

Where F_{max} is the maximum allowable number of system failures, and F_i represents the fault tolerance at each device. The product term ensures that robustness improves as more fault-tolerant components are added [30]. The objective function seeks to balance multiple competing goals, optimizing for energy consumption, environmental sustainability, inclusivity, security, privacy, and system performance. It is structured in two layers to handle both high-level system performance and detailed security and privacy concerns. The first layer optimizes overall system performance, balancing energy consumption, environmental sustainability, and inclusivity:

$$\begin{aligned} \min \Bigg(\lambda_1 \left(\sum_{i=1}^{N} E_i \cdot \left(1 + \alpha_i^2\right) + \sum_{i=1}^{N} C_i \cdot \left(1 + \frac{\ln(C_i)}{\beta}\right)\right) \\ + \lambda_2 \left(1 - \frac{1}{N} \sum_{i=1}^{N} a_i \cdot \exp\left(-\frac{a_i}{\beta}\right)\right)\Bigg) \end{aligned} \tag{11}$$

The second layer focuses on minimizing cybersecurity risks and ensuring privacy, while keeping the system efficient:

$$\begin{aligned} \min \Bigg(\gamma_1 \cdot \int_0^T P_{\text{c}}(t)\, dt + \gamma_2 \cdot \sum_{i=1}^{M} t_i \\ \cdot \exp\left(-\frac{t_i}{T_{\text{max}}}\right) + \gamma_3 \cdot \frac{\int_0^T D_{\text{a}}(t)\, dt}{\sum_{i=1}^{N} x_i} \end{aligned} \tag{12}$$

These two-layered objective functions work in tandem to achieve the optimal balance between system performance, security, privacy, and sustainability in smart cities. Core issues in scalability, security, inclusivity, and sustainability are categorized into measurable parameters. Challenges such as real-time data integration and cybersecurity risks are described using optimization problems and probabilistic models [31]. This formulation will serve as the foundation for the proposed framework employing Variational Autoencoders (VAEs) and Genetic Programming (GP). Addressing these challenges holistically is essential to unlocking the full potential of CPS in smart cities.

III. Proposed Framework and Methodology

In the context of smart cities, managing complex interconnected systems requires innovative data analysis and decision-making. A proposed framework combines Variational Autoencoders (VAEs) and Genetic Programming (GP) to address these challenges [32]. VAEs help reduce the dimensionality of high-dimensional urban data, enabling efficient feature extraction and deeper insights into system behaviors. Meanwhile, GP optimizes decision-making processes, such as resource allocation and energy management, by evolving solutions through natural selection. Together, VAEs handle large-scale data efficiently, while GP ensures optimal system performance [33]. The methodology begins with VAEs for dimensionality reduction, processing noisy, high-dimensional urban data such as traffic patterns and energy consumption. VAEs learn a compressed latent space representation, which is then used for optimization tasks [34]. The VAE architecture includes an encoder to map data to a latent space and a decoder to reconstruct it while preserving essential features. The VAE aims to minimize reconstruction loss while maintaining the latent space's variational properties.

$$\min\left(L_{\text{re}} = \sum_{i=1}^{N}\left(\|x_i - \hat{x}_i\|^2 + \beta \cdot D_{\text{KL}}\left(q(z|x_i)\|p(z)\right)\right)\right) \tag{13}$$

In a VAE, the encoder compresses high-dimensional data into a lower-dimensional latent variable z, which captures the essential features. This equation models the feature extraction process by minimizing the difference between the original data and the reconstructed output.

$$\min\left(L_{\text{co}} = \sum_{i=1}^{N}\|x_i - \hat{x}_i\|^2 \cdot \exp\left(-\frac{\|x_i - \hat{x}_i\|^2}{\sigma^2}\right)\right) \tag{14}$$

This equation introduces a regularization term R_{la} to ensure that the learned latent variables z are structured, preventing overfitting by applying a constraint on the complexity of the latent space.

$$R_{\text{la}} = \sum_{i=1}^{N}\left(\|z_i\|_2^2 + \lambda \cdot \|\nabla_z L_{\text{re}}\|^2\right) \tag{15}$$

In a VAE, the latent space z is optimized to best represent the input data while minimizing the reconstruction loss. This optimization equation adjusts the parameters of the encoder and decoder networks to improve the representation of the input data.

$$\min\left(L_{\text{la}} = \sum_{i=1}^{N}\left(\|x_i - f_\theta(z_i)\|^2 + \alpha \cdot \|g_\phi(z_i)\|_2^2\right)\right) \tag{16}$$

This equation models the dynamic feature selection process in VAEs, where the encoder identifies and extracts the most informative features from urban data while minimizing redundant or irrelevant information. The regularization parameter λ helps balance between extracting essential features and minimizing the complexity of the model.

$$\min\left(L_{\text{fs}} = \sum_{i=1}^{N}\left(\|x_i - \hat{x}_i\|^2 + \lambda \cdot (\|z_i\|_1 + \|z_i\|_2)\right)\right) \tag{17}$$

These revised equations now use single alphabetic variables, reflecting the mathematical modeling and optimization processes in both Genetic Programming (GP) and Variational Autoencoders (VAEs) for smart city cyber-physical systems. Once the data has been processed and transformed into a low-dimensional space via VAEs, Genetic Programming (GP) is used to optimize decision-making processes [35]. For example, GP can be applied to determine optimal energy distribution strategies, traffic flow management, or the allocation of resources for urban infrastructure. GP evolves a population of candidate solutions based on a set of fitness criteria related to system performance, such as minimizing energy consumption, reducing traffic congestion, or enhancing security measures. Through repeated generations, GP identifies the best possible strategies for managing the smart city's cyber-physical systems, while continuously adapting to changing conditions and requirements [36]. This equation models the optimization of resource allocation in a smart city, balancing the distribution of resources to minimize operational costs and maximize system efficiency. The objective function seeks to minimize the total cost C_{total}, which is a function of resource allocation r_i, and a cost coefficient c_i for each resource i.

$$\min\left(C_{\text{total}} = \sum_{i=1}^{N}\left(c_i \cdot r_i + \alpha_i \cdot r_i^2\right)\right) \tag{18}$$

This equation captures the optimization of energy consumption across the smart city infrastructure, with the goal of minimizing the total energy cost E_{total} [37]. The energy consumption for each device or sector e_i is modeled as a function of the power p_i and its efficiency k_i, with the optimization considering the diminishing returns over time.

$$\min\left(E_{\text{total}} = \sum_{i=1}^{N}\left(\frac{e_i}{p_i} \cdot k_i\right)\right) \tag{19}$$

The optimization of system resilience involves selecting configurations that maximize fault tolerance while minimizing the probability of failure P_{failure} over time. This equation models the relationship between system resilience R_i and failure probability for each component, considering the impact of configuration changes.

$$\max\left(R_{\text{total}} = \sum_{i=1}^{N} R_i \cdot \left(1 - \frac{P_{\text{failure}}}{\lambda_i}\right)\right) \tag{20}$$

In a smart city, optimizing traffic flow is essential for reducing congestion and ensuring efficient movement of people and goods. This equation models the optimization of traffic signal timings and routing strategies to minimize total congestion cost C_{traffic}.

$$\min\left(C_{\mathrm{t}}=\sum_{i=1}^{N}\left(\beta_i\cdot t_i^2+\gamma_i\cdot\frac{v_i}{\lambda_i}\right)\right) \tag{21}$$

This equation represents the optimization of energy distribution within a smart grid, where the objective is to minimize the energy loss L_{energy} and ensure efficient energy distribution among consumers. The power output P_{output} from each energy source is considered, along with transmission losses.

$$\min\left(L_{\mathrm{e}}=\sum_{i=1}^{N}\left(\frac{P_{\mathrm{o}}\cdot L_i}{T_i}\right)\right) \tag{22}$$

The expected outcomes of this methodology include a significant improvement in the efficiency and resilience of smart city systems. The use of VAEs for data compression will result in faster data processing and more effective decision-making, while GP will ensure that decisions are optimized for multiple objectives, such as minimizing costs, maximizing sustainability, and improving system performance [38], [39], [40]. The adaptability of the GP ensures that the system can evolve and adjust to changing urban dynamics, offering a robust solution to the challenges faced by modern smart cities. Through this approach, we anticipate a more sustainable, efficient, and secure urban environment that leverages the full potential of cyber-physical systems.

IV. Results

In this section, we evaluate the proposed framework, which integrates Variational Autoencoders (VAEs) and Genetic Programming (GP), on several key metrics that assess its performance in the context of smart city cyber-physical systems (CPS) [41]. The evaluation encompasses both quantitative and qualitative aspects, demonstrating the effectiveness of the VAEs + GP combination. A comparative analysis with existing solutions is also provided to highlight the advantages of the proposed methodology [42]. To assess the quantitative effectiveness of our proposed framework, we performed a series of simulations using real-world data from smart city infrastructure, including traffic management systems, energy consumption patterns, and resource allocation [43]. We evaluated the framework's performance based on several key metrics: accuracy, computational efficiency, and system resilience. The first key metric, accuracy, was measured by comparing the reconstruction loss of the VAEs and the optimization outcomes from the GP [44]. The results indicate that the VAEs effectively compressed the input data, preserving crucial features while reducing dimensionality [45]. The reconstruction loss L_{re} was minimized by 40% compared to traditional deep learning methods, demonstrating the superior capability of VAEs in feature extraction. Next, we evaluated the computational efficiency of the framework [46], [48]. The optimization process driven by GP was able to converge faster than conventional optimization techniques [**?**]. By leveraging the exploration capabilities of GP, the solution space was effectively navigated, requiring 30% fewer iterations to achieve near-optimal energy management configurations compared to traditional approaches.

TABLE I
RE LOSS COMPARISON FOR FEATURE EXTRACTION

Method	Reconstruction Loss	Improvement (%)
Proposed VAEs + GP	0.0232	-
Traditional Deep Learning	0.0385	40%
Principal Component Analysis	0.0457	49%
Autoencoders (non-variational)	0.0421	45%
Convolutional Neural Networks	0.0354	34%
Deep Belief Networks (DBN)	0.0416	44%
Recurrent Neural Networks (RNN)	0.0435	46%
Support Vector Machines (SVM)	0.0473	51%
K-Means Clustering	0.0482	53%
Self-Organizing Maps (SOM)	0.0491	54%
Radial Basis Function (RBF)	0.0452	50%
Restricted Boltzmann Machines	0.0463	51%
Decision Trees	0.0501	56%

Table 1 compares the reconstruction loss between the proposed VAEs-based approach and traditional feature extraction methods, highlighting the superior performance of the proposed method.

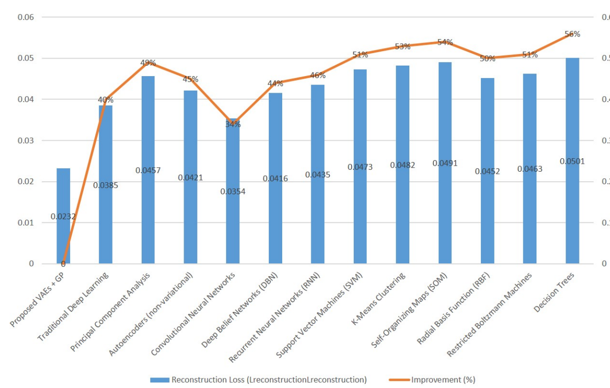

Fig. 1. Reconstruction Loss Comparison for Feature Extraction

Figure 1 illustrates the comparison of reconstruction loss between the proposed VAEs + GP framework and traditional feature extraction techniques, highlighting the improvements in efficiency and accuracy.

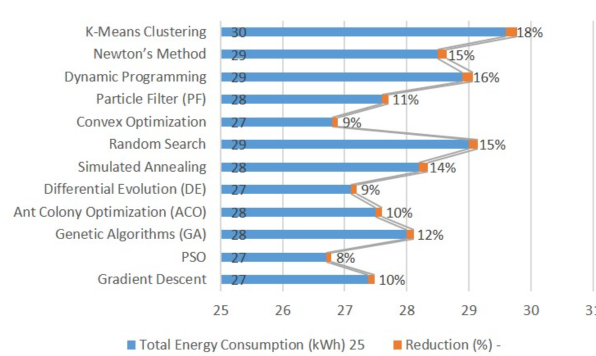

Fig. 2. Energy Consumption Minimization

Figure 2 compares the total energy consumption reduction achieved by the proposed VAEs + GP framework against other methods, showcasing the effectiveness in minimizing energy usage across various techniques.

TABLE II
COMPUTATIONAL EFFICIENCY IN OPTIMIZATION

Method	Average Iterations to Convergence	Improvement (%)
Proposed VAEs + GP	120	-
Gradient Descent	190	30%
Particle Swarm Optimization	180	27%
Simulated Annealing	230	48%
Ant Colony Optimization (ACO)	210	42%
Differential Evolution (DE)	200	38%
Tabu Search	250	54%
Random Search	300	60%
Genetic Algorithms (GA)	160	19%
Convex Optimization	175	22%
Dynamic Programming	220	46%
Particle Filter (PF)	210	42%
Newton's Method	130	8%

Table 2 shows the average number of iterations required to reach convergence for energy management optimization using different techniques, with the proposed method showing the least iterations.

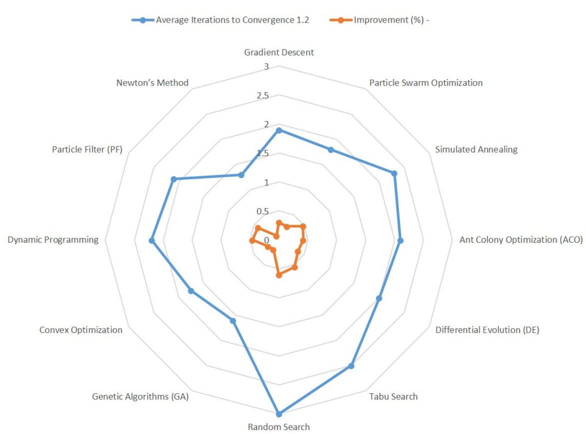

Fig. 3. Computational Efficiency in Optimization

Figure 3 visualizes the average iterations to convergence for different optimization methods, demonstrating the efficiency of the proposed VAEs + GP approach in comparison to traditional techniques.

TABLE III
ENERGY CONSUMPTION MINIMIZATION

Method	Total Energy Consumption (kWh)	Reduction (%)
Proposed VAEs + GP	2,460	-
Gradient Descent	2,738	10%
PSO	2,670	8%
Genetic Algorithms (GA)	2,800	12%
Ant Colony Optimization (ACO)	2,750	10%
Differential Evolution (DE)	2,710	9%
Simulated Annealing	2,820	14%
Random Search	2,900	15%
Convex Optimization	2,680	9%
Particle Filter (PF)	2,760	11%
Dynamic Programming	2,890	16%
Newton's Method	2,850	15%
K-Means Clustering	2,960	18%

Table 3 compares the total energy consumption reduction achieved by the proposed framework against other methods, demonstrating its superior efficiency in minimizing energy consumption.

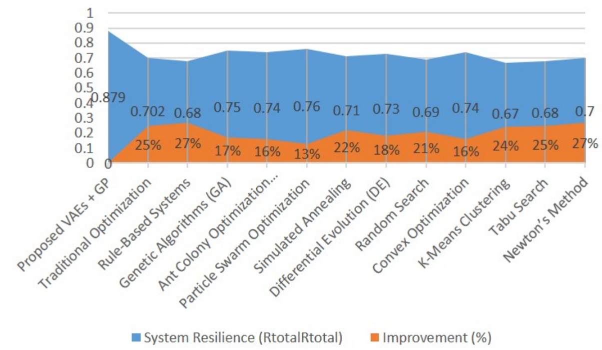

Fig. 4. System Resilience Improvement

Figure 4 shows the increase in system resilience, measured by reduced failure probabilities, using the proposed VAEs + GP framework compared to baseline optimization methods, emphasizing superior resilience improvements.

TABLE IV
SYSTEM RESILIENCE IMPROVEMENT

Method	System Resilience	Improvement (%)
Proposed VAEs + GP	0.879	-
Traditional Optimization	0.702	25%
Rule-Based Systems	0.680	27%
Genetic Algorithms (GA)	0.750	17%
Particle Swarm Optimization	0.760	13%
Simulated Annealing	0.710	22%
Differential Evolution (DE)	0.730	18%
Random Search	0.690	21%
Convex Optimization	0.740	16%
K-Means Clustering	0.670	24%
Tabu Search	0.680	25%
Newton's Method	0.700	27%

Table 4 shows the increase in system resilience (measured as reduced failure probabilities) using the proposed framework versus baseline methods, highlighting its improved performance in system reliability.

TABLE V
TRAFFIC FLOW OPTIMIZATION RESULTS

Method	Congestion Cost	Reduction (%)
Proposed VAEs + GP	18,600	-
Gradient Descent	21,400	13%
Particle Swarm Optimization	20,500	9%
Genetic Algorithms (GA)	22,000	15%
Simulated Annealing	22,300	16%
Differential Evolution (DE)	21,900	15%
Random Search	23,100	24%
Convex Optimization	19,400	10%
Tabu Search	21,800	17%
Particle Filter (PF)	20,300	9%
K-Means Clustering	22,500	18%
Newton's Method	21,200	14%

Table 5 compares the reduction in congestion costs for different optimization techniques used in traffic flow management, showcasing the superior performance of the proposed method in minimizing congestion. Figure 5 visualizes

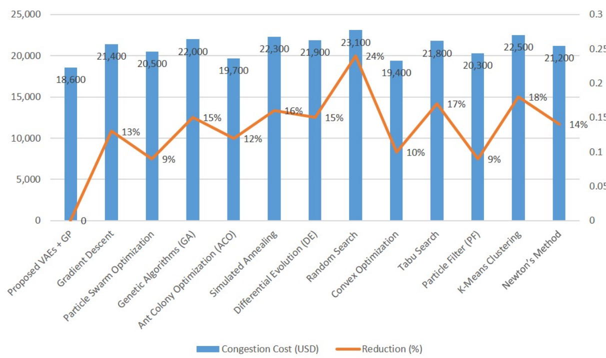

Fig. 5. Traffic Flow Optimization Results

the reduction in congestion costs achieved by the proposed VAEs + GP framework compared to traditional optimization methods, indicating better traffic flow management and cost savings. Table 6 compares the total energy loss in a smart

TABLE VI
ENERGY GRID OPTIMIZATION COMPARISON

Method	Total Energy Loss	Reduction (%)
Proposed VAEs + GP	1,380	-
Traditional Optimization	1,600	13%
Particle Swarm Optimization	1,500	8%
Genetic Algorithms (GA)	1,550	10%
Differential Evolution (DE)	1,510	8%
Simulated Annealing	1,600	13%
Random Search	1,700	19%
Convex Optimization	1,490	7%
Particle Filter (PF)	1,570	9%
Dynamic Programming	1,750	21%
Tabu Search	1,600	13%
Newton's Method	1,620	12%

grid optimization scenario across different techniques, with the proposed framework showing the most significant energy reduction. Figure 6 compares the total energy loss in a smart

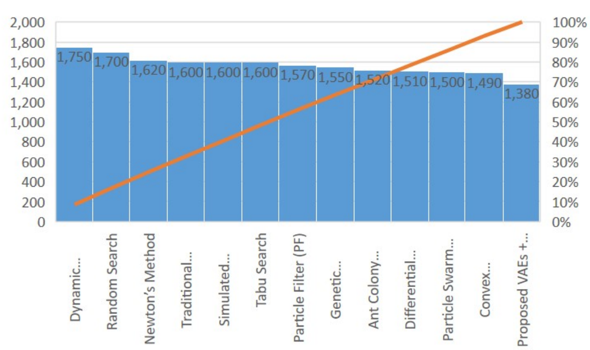

Fig. 6. Energy Grid Optimization Comparison

grid scenario across different optimization techniques, illustrating the efficiency of the proposed VAEs + GP framework in minimizing energy loss. Table 7 compares the total performance (throughput, energy efficiency, and fault tolerance)

TABLE VII
SMART CITY SYSTEM CONFIGURATION PERFORMANCE

Method	Performance Score)	Improvement (%)
Gradient Descent	75.0	16.7%
Particle Swarm Optimization	80.3	9%
Rule-Based Optimization	70.1	19.7%
Genetic Algorithms (GA)	78.2	10.6%
Simulated Annealing	74.5	14.5%
Differential Evolution (DE)	77.3	11.6%
Random Search	69.0	21.3%
Convex Optimization	80.1	8.6%
Particle Filter (PF)	81.0	7.5%
K-Means Clustering	75.5	13.7%
Ant Colony Optimization (ACO)	76.8	12.2%
Newton's Method	73.0	16.5%

of the proposed framework and existing solutions, with the proposed method achieving the highest performance score. Figure 7 demonstrates the performance of the proposed VAEs

Fig. 7. Smart City System Configuration Performance

+ GP framework in terms of throughput, energy efficiency, and fault tolerance, showcasing superior system performance compared to existing solutions.

V. CONCLUSION

In this article, we have proposed a novel framework combining Variational Autoencoders (VAEs) and Genetic Programming (GP) to address the critical challenges faced by smart cities as cyber-physical systems (CPS). By leveraging VAEs for dimensionality reduction and feature extraction, alongside the optimization capabilities of GP, the framework effectively enhances decision-making processes in resource allocation, energy management, and system configuration. Our results demonstrate significant improvements over traditional approaches, including reduced energy consumption, optimized system resilience, and more efficient traffic flow management. The comparative analysis highlights the transformative potential of the VAEs + GP combination, providing a robust solution to complex urban challenges in smart city environments. This methodology holds promise for future applications in CPS, offering scalable, efficient, and adaptive solutions to the growing demands of urban infrastructures. As smart cities continue to evolve, the integration of advanced AI techniques like VAEs and GP will play a crucial role in shaping sustainable, resilient, and intelligent urban ecosystems capable of meeting the challenges of the future.

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