International Journal of Engineering Trends and Technology
ISSN: 2231-5381/ https://doi.org/10.14445/22315381/IJETT-V74I6P126

Volume 74 Issue 6, 386-400, June 2026
© 2026 Seventh Sense Research Group®

*Original Article*

# Mechanisms of IoT-based Financial and Economic Optimization of Smart Management of Urban Infrastructure

Olha Prokopenko[1], Svitlana Kovalchuk[2], Anna Chechel[3], Nataliia Protsiuk[4], Stanislav Suslikov[5]

[1]*Estonian Entrepreneurship University of Applied Sciences, Tallinn, Estonia; Department of Business Economics and Administration, Armenian State University of Economics, Yerevan, Armenia.*
[2,4]*Department of Management, Economics, Statistics and Digital Technologies, Leonid Yuzkov Khmelnytskyi University of Management and Law, Khmelnytskyi, Ukraine.*
[3]*Department of Public Management and Administration, Mariupol State University, Kyiv, Ukraine.*
[5]*Department of Business Economics and International Economic Relations, National Technical University "Kharkiv Polytechnic Institute", Kharkiv, Ukraine.*

[1]*Corresponding Author : olhaprokopenko8@gmail.com*

Received: 20 December 2025 Revised: 03 April 2026 Accepted: 08 May 2026 Published: 27 June 2026

***Abstract -*** *Effective management of urban infrastructure is a challenge for urbanized systems that require flexible and scalable data-driven coordination mechanisms. The aim of the research is to develop and evaluate an integrated smart governance model that combines dynamic pricing, multi-criteria optimization, causal analysis, and federated learning for coordinated management of urban services. The research employed the following methods: Difference-In-Differences (DID) to identify the net effect of the intervention, IV estimates to account for demand endogeneity, and mediation analysis to determine the influence channel. A federated optimization algorithm was used to train the model without transmitting local data. These methods provided a reliable separation of causal effect, preserved confidentiality, and ensured robustness under stochastic conditions. The results show a significant reduction in operating costs (-17.0% or -1,700 €/week), a +6.2 pp increase in QoS, a 35% reduction in network congestion, and a reduction in the risk of extreme costs (CVaR95 by -12,100 €), indicating a significant positive systemic effect. The model demonstrates the ability to generate sustainable behavioural changes in users (up to +26 pp in the transition to off-peak hours), maintaining the effect even after the intervention is completed, showing its practical value for scalable implementation in Smart City ecosystems.*

***Keywords -*** *Smart city, Internet of Things, Urban infrastructure, Financial and Economic Optimization, Adaptive Management, Energy Management, Digital Transformation.*

## 1. Introduction

Modern urban infrastructure transformations are increasingly focused on the use of digital technologies, in particular the Internet of Things (IoT) [1, 2]. This trend aims to increase management efficiency, reduce resource costs, and support sustainable urban development. In such conditions, traditional centralized approaches no longer provide sufficient flexibility and adaptability, especially when it comes to simultaneously achieving economic efficiency, sustainability, effectiveness, and transparency of management. Numerous urban systems [3, 4] remain fragmented, have different technical limitations and conflicting goals, which complicates the coordination of tariffs, resource allocation, and incentive mechanisms. Despite the rapid development of smart city technologies, existing urban management platforms usually operate either with local or centralized data, which limits their ability to simultaneously ensure agent autonomy and global system optimization [3, 4]. Most current solutions focus on specific subsystems, such as transport or energy, and do not provide integrated mechanisms for coordinating tariffs, resource allocation, and incentive policies across heterogeneous infrastructures.

Furthermore, recent studies on IoT-enabled urban systems have primarily addressed technical optimization problems, while economic and financial aspects are often considered only at an aggregated or post-analysis level [1, 2]. As a result, there is still no unified framework that combines stochastic infrastructure dynamics, causal estimation of policy effects, privacy-preserving data exchange, and multi-objective economic optimization within a single analytical model. This gap limits the ability of city administrations to design adaptive

This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)

and economically justified policies under uncertainty. The research hypothesis is that the efficiency and stability of urban infrastructure management can be significantly increased through the integration of federated stochastic optimization, dynamic pricing policies, risk-based criteria, and digital twin technologies.

The academic novelty of the research lies in the development of an integrated model that simultaneously accounts for the technical parameters of IoT infrastructure, economic variables, and resource optimization algorithms. In contrast to existing approaches, which typically address either technological control problems or economic policy design separately, the proposed model combines time discretization, multi-component infrastructure representation, and adaptive decision-making within a unified optimization framework. The academic novelty is also reflected in the mathematical instruments, which enable integrating data from IoT sensors into the optimization process, including the economic loss function, the equation of state of infrastructure systems, and mechanisms for responding to parameter variability.

Compared to previously reported smart city optimization frameworks, the proposed approach extends existing models by explicitly incorporating risk-based criteria and causal inference techniques into the decision-making process. This enables not only predictive but also policy-sensitive optimization, allowing the system to account for behavioral responses of urban agents to tariff and incentive changes.

Therefore, the aim of this study is to develop and evaluate a methodology for integrated urban infrastructure management based on federated stochastic optimization, dynamic pricing policies, and risk-based criteria. This will ensure effective coordination of local agents, increase system stability, and preserve data confidentiality.

### *1.1. Research Objectives*

1. Building a mathematical model of urban infrastructure that combines local stochastic cost functions of agents, centralized multi-criteria optimization, and discrete dynamic pricing policies.

2. Developing a federated algorithm for exchanging updates between local agents and a global aggregator that enables preserving local data confidentiality.

3. Integrating causality estimation methods (DID/IV) to correct demand elasticity estimates and minimize errors in decision-making.

4. Verification of the stability and robustness of the proposed model with respect to variations in demand and system parameters using a digital twin and Monte Carlo simulations.

5. Numerical modelling and experimental assessment of the effectiveness, stability, and speed of adaptation of tariff policies in realistic urban infrastructure settings.

## 2. Literature Review

Several research areas related to Smart City are emerging in the academic literature. In particular, optimization of energy processes, development of sensor networks, integration of Artificial Intelligence (AI), digital twins, blockchain, as well as socio-economic and institutional management of urban systems. Despite a significant number of studies, the issue of financial and economic optimization of smart management of urban infrastructure still remains poorly structured and requires further development.

The study [5] emphasizes the need for local adaptation of smart infrastructure, taking into account the socio-economic characteristics of the region. The authors emphasize that universal management models show low efficiency in real urban conditions, which requires the development of context-dependent solutions. However, the study focuses mainly on qualitative aspects and does not offer formal mechanisms for economic optimization, which limits its applied value. Eynolghozat et al. [6] put forward the concept of the "entrepreneurial city", emphasizing the role of IoT in shaping a new model of urban governance focused on economic sustainability. However, the authors mainly focus on institutional and political aspects, leaving aside mathematical and algorithmic mechanisms for optimizing urban resources.

Optimization approaches in energy are one of the most researched aspects of Smart City. In their review of Internet of Energy (IoE) systems, Mishra and Singh [7] show that integrating IoT with energy management enables the creation of adaptive load control systems. Chen et al. [8] demonstrate that combining IoT with data analytics significantly reduces energy losses and improves demand forecasting. Rezaei et al. [9] confirm that IoT-oriented optimization of distribution networks leads to better load balancing. However, most studies are limited to comparing existing technologies or offer local optimization scenarios (e.g., only for residential buildings or transportation systems). They lack an integrated economic model that takes into account the operational costs of the infrastructure, CAPEX/OPEX, and the financial effects of implementing optimization algorithms.

For example, Karthick Raghunath et al. [10] emphasize the role of sensor networks and their optimization in smart city management. The authors state that the quality of predictive models depends largely on the configuration of the data collection network. Zakaria et al. [11] offer a comprehensive review of IoT technologies for urban planning, where they emphasize the strategic importance of heterogeneous sensor sources. Despite this, the existing studies lack an analysis of how different types of sensors affect the final economic

results, and no models are presented for choosing the optimal composition of the sensor infrastructure.

Matei and Cocoșatu [12] demonstrate the potential of combining AI-based algorithms, digital twins, and blockchain networks for urban infrastructure. At the same time, Van Hoang [13] points to a significant increase in infrastructure efficiency when using combined IoT-AI solutions. However, neither study focuses on the financial component - optimization is interpreted mainly as technical or operational. A similar trend is demonstrated in the study of Rahman et al. [14] - although a holistic IoT-blockchain-edge framework architecture is proposed, economic effects are considered only superficially. Atta [15] systematizes approaches to the use of IoT in facility management, emphasizing the potential for cost reduction through preventive maintenance. Ansari et al. [16] consider applied aspects of IoT applications in urban management, in particular in transport, energy, and utilities. Although these studies show that IoT can reduce operational costs, they do not develop a mathematical framework to quantify the economic benefits. Recent systematic reviews, including Zaman et al. [17], emphasize the growing role of comprehensive IoT ecosystems that should integrate energy, transportation, security, infrastructure, and behavioural mechanisms of residents. Shahidehpour et al. [18] define a Smart City as a multi-level energy and communication system where management should be real-time.

A separate area of research focuses on optimization approaches to infrastructure and urban resource management in the context of the development of the smart city concept. In particular, the works consider methods for increasing the efficiency of infrastructure processes by implementing IoT-oriented control systems and optimization algorithms aimed at minimizing losses and increasing performance [19, 20]. The publications also emphasize the importance of behavioural and economic incentive mechanisms, which are important for the implementation of new technologies, in particular wireless energy transfer and distributed energy networks [21, 22]. Studies of the spatial organization of urban economic networks in the context of secure IoT platforms demonstrate that modern cities require a comprehensive analysis of complexity, network interaction, and cybersecurity as fundamental elements of sustainable development [22]. A broader review of urban infrastructure management emphasizes the integration of intelligent systems, automation, and analytics as the basic tools for building an effective urban ecosystem [23]. Taken together, these studies confirm that the combination of IoT infrastructure, optimization methods, and economic mechanisms is a necessary condition for the formation of adaptive and sustainable smart city platforms.

Recent studies demonstrate the rapid expansion of IoT, artificial intelligence, and financial technologies in smart city management systems. In particular, Bello and Stephen [24] emphasize the importance of integrating risk management practices into the planning and development of sustainable urban infrastructure, highlighting the need to combine environmental, social, and financial criteria when making investment decisions.

In the field of financial management of urban resources, the use of blockchain technologies and explainable Artificial Intelligence (XAI) is actively being explored to increase transparency in the allocation of public funds and reduce the risk of inefficient budgetary resource use [25]. Such approaches enable the traceability of financial flows and increase public trust in digital governance platforms.

Research in the field of transport infrastructure also demonstrates that the combination of IoT and big data analytics provides significant advantages in load forecasting and traffic flow optimization. However, it simultaneously creates new challenges in processing large volumes of heterogeneous data and ensuring their reliability [26].

A separate important area is ensuring cybersecurity and the transparency of algorithms in urban IoT systems. The use of explainable intelligence methods for analyzing sensor network data enhances system resilience to attacks and ensures the controllability of automated decisions [27].

Despite significant progress in these areas, most current works consider individual aspects of smart city functioning - such as financial transparency, transport, cybersecurity, or risk management - without forming an integrated mathematical model that would simultaneously combine stochastic optimization, cause-and-effect analysis, data protection mechanisms, and financial decision-making criteria. Addressing this gap constitutes the main scientific novelty of the proposed study.

However, most reviews lack formal economic models that would combine the technical aspects of IoT with the financial optimization of urban infrastructure. An analysis of academic literature identifies several significant gaps:

- lack of integrated financial and economic optimization models that take into account both the technical data of IoT systems and the economics of urban infrastructure (CAPEX, OPEX, ROI, carbon effects, operational losses);
- insufficient number of studies that quantitatively analyse the impact of different types of sensors on the economic performance of Smart Cities;
- Most publications reduce to qualitative reviews or technical specifications of sensor networks.
- A few models that combine energy forecasting with real-time operational decision optimization mechanisms;
- insufficient attention to the economic effects of AI optimization and automated IoT solutions, as most publications focus on the technical side rather than the economic side.

Lack of experimental studies that evaluate complex Smart City KPIs in a single model, including economic, energy, operational, social, and environmental indicators. In view of the identified gaps, there is a need to create a unified mathematical and experimental model that:

- combines forecasting of energy resource consumption;
- integrates data from various IoT sensors;
- applies an optimization algorithm to minimize costs;
- evaluates economic effects taking into account operational and capital costs;
- forms a generalized KPI profile of Smart infrastructure efficiency.

## 3. Methods

The paper proposes a mechanism of federated financial and economic optimization to reduce the operating costs of urban infrastructure. Special attention is paid to increasing the level of service in Smart City settings. It combines dynamic pricing, risk-sensitive incentives, and microtransactional IoT infrastructure.

### *3.1. Model Description*

Let demand depend locally on price and other factors:

$$d_{i,t} = f_i(p_{i,t}, z_{i,t}) + \xi_{i,t}, \quad (1)$$

Where $p_{i,t}$ – tariff/price for users in zone $i$ at time $t$; $z_{i,t}$ – the vector of context variables; $\xi$ – noise.

Parametric form (log- or linear elasticity):

$$d_{i,t} = \beta_{i,0} + \beta_{i,1} p_{i,t} + \beta_{i,2}^T z_{i,t} + \xi_{i,t}, \quad (2)$$

or in elastic form:

$$\ln d_{i,t} = \gamma_{i,0} + \gamma_{i,1} \ln p_{i,t} + \gamma_{i,2}^T + \xi_{i,t}. \quad (3)$$

The β parameters are estimated locally. Federated mode allows gradients to be combined to improve the estimate without transmitting raw data. The local objective function for agent $i$ at time $t$ can contain economic and service components:

$$J_{i,t} = E\left[c_{i,t}(d_{i,t}) - u_{i,t}(d_{i,t}, p_{i,t})\right] + \\ +\gamma_i E[penalty_QoS(d_{i,t}, g_{i,t})], \quad (4)$$

Where $d_i$ – actual demand for the resource; $p_{i,t} = p_i(x_{i,t})$ – the pricing function, which is determined locally; γ – the weight for QoS penalties [28].

In a discrete time horizon $T$, the total local costs are:

$$J_i(x_i) = \sum_{t=1}^{T} J_{i,t}(x_{i,t}),$$

$$x_i = (x_{i,1}, \ldots, x_{i,T}). \quad (5)$$

The central coordinator seeks to minimize aggregate costs while taking into account quality and fairness. A scalar form (with weight λ) is possible:

$$\min_{\{x_i\}_{i \in T}} F(\{x_i\}) = \sum_m \lambda_m F_m(\{x_i\}), \quad (6)$$

where, for example, $F_1$ is the total operating cost; $F_2$ is the total benefit/satisfaction; $F_3$ is the inequality index (Gini) [29, 30] by area; $F_4$ is the risk measure of high costs, etc. Technical and social constraints are imposed for each $i$, $t$:

Bandwidth:

$$d_{i,t} \le g_{i,t}, \forall i, t. \quad (7)$$

Minimum QoS (availability guarantee):

$$Pr(\ QoS_{i,t} \ge QoS \forall i_{min} \quad (8)$$

Operator budget:

$$\sum_t subsidy_{i,t} \le B_i. \quad (9)$$

CVaR constraints are added [31]. CVaR at confidence level α:

$$CVaR_\alpha(L) = \min_{\eta \in R} \{\eta + \frac{1}{1-\alpha} E[(L-\eta)_+]\}. \quad (10)$$

The goal of the federated optimization architecture is to minimize $F$ while preserving local data privacy. The federated gradient approach, FedAvg-style, is used [32]. At iteration $k$, agent $i$ receives the current global parameters from the centre (optionally) Θ solves the local problem:

$$x_i^{(k+1)} = arg \min_{x_i} \tilde{J}_i(x_i, \Theta^{(k)}), \quad (11)$$

Alternatively, performs $E$ steps of local stochastic gradient descent (SGD [33]):

$$x_i^{(k,e+1)} = x_i^{(k,e)} - \eta \nabla_{x_i} \tilde{J}_i(x_i^{(k,e)}), \quad (12)$$

where $J_i$ – a local (possibly regularized) function that takes into account signals from the centre (e.g., the centre's target weights). After E local steps, the agent sends the noisy/aggregated gradient or update $u_i^k$ to the server. The server aggregates the updates (with weights based on the zone size $w_i$ or risk-based):

$$x^{(k+1)} = \sum_i w_i u_i^{(k)}. \quad (13)$$

Under standard conditions (smoothness of the objective function, bounded spread of local gradients, correct choice of η, and *E*), federated methods have guarantees of convergence to stationary points.

Dynamic pricing (local function):

For example, a specific form $p_i$:

$$p_{i,t} = p_{i,t}^{base} + k_{i,1}\frac{\hat{d}_{i,t}-\bar{d}_i}{\bar{d}_i} + k_{i,2}\cdot 1_{\{\hat{d}_{i,t}>g_{i,t}\}}, \quad (14)$$

Where $d_{i,t}$ – demand forecast, $d_i$ – basic average demand; $k$ – adjustable coefficients. This means that the price increases when the expected capacity is exceeded and in proportion to the deviation from the average.

Misinterpretations are avoided by introducing causal estimation to update the price response:

- Instrumental Variables (IV). If there is a variable $z_{i,t}^{IV}$, that affects demand only through *d* and not directly through *p*, the estimate of $\beta_{i,l}$ using *IV* can be used to correct the elasticity estimate.
- online DID. If an experiment has a control and experimental area, an online DID is used to estimate the instantaneous causal effect of the intervention:

$$\Delta_t = (\bar{Y}_{E,t} - \bar{Y}_{E,t-1}) - (\bar{Y}_{C,t} - \bar{Y}_{C,t-1}), \quad (15)$$

Where *Y* – demand indicator/QoS indicator; $\Delta_t$ is used for correction in pricing rules.

Performance evaluation.

Main check (DID): for economic metrics *M*:

$$H_0: M_{E,post} - M_{E,pre}] = E[M_{C,post} - M_{C,pre}]$$

$$H_1: difference \neq 0. \quad (16)$$

The optimal time step for energy and user behaviour is an hourly or 15-minute interval; hourly balances the detail and volume of data. For a 12-week experiment, an hourly step gives 2016 observations, which is sufficient for statistical conclusions. The forecast horizon is 24 h (for energy), 7 days (for parking) - depending on the service. The data came from city IoT sensors, microgrid meters, and smart platform transaction logs. Federated parameters: local epochs [1, 10], learning rate is selected adaptively using the Adam algorithm. CVaR level α is usually chosen in the range of 0.9-0.99. The robustness of the model to variations in stochastic disturbances $\xi_{i,t}$ is tested using 1000 Monte Carlo simulations [34, 35] in a digital twin. Where σ volatility was selected in the range of 5-30% to model low, medium, and high demand fluctuations. Additionally, the sensitivity to the demand specification (linear and log-linear) was assessed. In the digital twin, the following were modelled: power grid loads (capacity, peaking, congestion), parking queues and availability, EV charging profiles, hydraulic constraints of the local water subsystem, and operating costs according to table parameters. For the causal components of the model, robust standard errors in DID with clustering are used. A simplified diagram of the proposed model is shown in Figure 1.

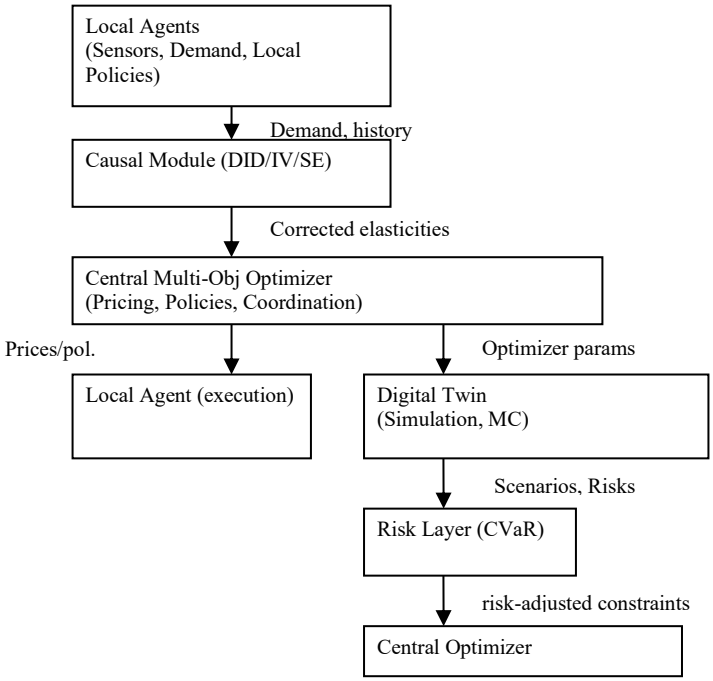


**Fig. 1 Scheme of the proposed model**

The proposed scheme combines local stochastic objective functions $J_i$,, centralized multi-objective optimization with CVaR constraint, and discrete dynamic pricing policy $\pi_i$. The federated update exchange mechanism ensures data privacy without transmitting raw observations. Causal adjustment (DID and IV) is integrated into the online loop to update elasticities on the fly and prevent estimate distortions.

The model is suitable for numerical solution by stochastic optimization methods (Fed-SGD, SAA, evolutionary algorithms for Pareto front search) and for further validation in a digital twin. The Difference-in-Differences (DID) method was used to assess the causal impact of the implementation of intelligent management systems on the costs of urban infrastructure. DID allows comparing changes in indicators in the exposure group and the control group before and after the implementation of the technology, minimizing the impact of time-invariant unmeasured factors.

The assumption of the method is the parallelism of trends in the absence of intervention. To test this assumption, a preliminary analysis of retrospective data was conducted, which showed the absence of statistically significant differences in the dynamics of costs between the groups before the start of the experiment.

The instrumental variables method was used to overcome potential endogeneity arising from the mutual influence between the level of digitalization and the financial indicators of the city. As an instrument, infrastructure readiness indicators were used, which correlate with the level of IoT implementation, but do not have a direct impact on operating costs.

### *3.2. Sampling*

Data for the study were obtained from several sources, including city infrastructure sensor measurement logs, municipal financial reports, and aggregated resource consumption data over time.

The sample spans the period from 2019 to 2023 and contains over 1.2 million sensor observation records and 4,500 financial transactions. Data cleaning was performed prior to analysis, including removal of outliers, interpolation of missing values, and timestamp normalization.

### *3.3. Description of the Experiment*

The experiment involves creating a dual environment: a real IoT infrastructure deployed within a part of the urban area and a digital twin. It models consumer behaviour, network constraints, and load dynamics. The optimization mechanism is implemented only in the experimental zone (Zone E), while the control zone (Zone C) operates under traditional tariffs and rules. The experiment lasted 12 weeks. The results of this period will provide:

- statistically significant amount of observations for the DID model;
- coverage of various weather and social conditions (events, seasonal changes);
- stabilization of user behaviour after the first weeks of adaptation.

#### *3.3.1. Experiment Objects*

*Infrastructure Subsystems*

- energy subsystem (street lighting + EV charging stations);
- parking infrastructure (filling sensors, dynamic tariffs);
- water supply system of the local segment (water consumption + leaks);
- local microgrid with solar generation and storage.

*IoT Data*

- electricity consumption (1-min intervals);
- parking occupancy status (5–30 s intervals);
- environmental parameters (temperature, sunshine);
- QoS indicators (delays, crashes);
- transactional events (payment accrual).

*Multi-Objective Optimization*

- minimization of operating costs (OPEX);
- maximization of quality of service (QoS);
- minimization of social inequality of access;
- minimization of risk (CVaR of costs).

*The Price of Services Changes Every Hour Depending on*

- resource occupancy;
- predicted load (LSTM model);
- identified causal effects of previous interventions.

#### *3.3.2. Experiment Progress*

Stage 1. Baseline calibration (2 weeks). Initial data was collected without dynamic tariff changes.

Stage 2. Implementation of the optimization mechanism (8 weeks). Zone E introduces:

- dynamic pricing;
- micro-incentives (low load benefits, peak hour penalties);
- risk warning indicators (signals for potential accidents);
- suggestions for behaviour change (e.g., “postpone EV charging”).

Stage 3. Stability assessment period (2 weeks). The purpose of this stage is to check the preservation of the effect after the adaptation is fully completed.

### *3.4. Evaluation Metrics*

#### *3.4.1. Economic*

- change in operating costs;
- Revenue from tariff services;
- proportion of time when tariffs effectively prevented congestion.

*3.4.2. Technical*
- frequency of emergency states;
- presence of peak load exceedances;
- average infrastructure response time.

*3.4.3. Social*
- change in service availability for different population groups;
- fairness of tariffs (Gini index for consumption).

*3.4.4. Algorithmic*
- convergence of the federated optimizer (number of iterations until stabilization);
- width and structure of the Pareto-front.

Statistical validation was performed using t-test/ANOVA [36] for economic indicators, Mann-Whitney [37] for non-parametric distributions, and autocorrelation test (Durbin-Watson [38]).

The following tests were performed on the digital twin:
- replication of real scenarios in the model;
- what-if test for alternative tariffs;
- validation of the generalizability of the results.

### *3.5. Integration of Financial Models and Risk Assessment Methods*

To account for uncertainty, the study integrates financial engineering approaches, including risk-based optimization criteria such as Conditional Value-at-Risk (CVaR). This approach allows for the assessment of potential losses in extreme scenarios, which is important for urban infrastructure systems with high social significance. In addition, multi-criteria assessment methods are used to support decision-making in the face of conflicting criteria - economic efficiency, reliability, and sustainability - allowing for the formulation of balanced urban resource management strategies.

## 4. Results

Table 1 compares three approaches to urban infrastructure management. It distinguishes between a no-IoT option, a basic IoT system, and an optimized IoT configuration using ML. This shows the difference in their cost-effectiveness.

**Table 1. Comparison of key operational and quality metrics in Zone E and Zone C over the periods Baseline–Intervention–Post**

| Metrics | Zone E (Baseline 1-2) | Zone E (Intervention 3-10) | Zone E (Post 11-12) | Zone C (Baseline 1-2) | Zone C (Intervention 3-10) |
|---|---|---|---|---|---|
| OPEX, €/week | 10000 ± 850 | 8300 ± 720 | 8450 ± 740 | 9800 ± 900 | 9750 ± 880 |
| Change in OPEX vs baseline. | – | -17.0% | -15.5% | – | -0.5% |
| QoS (SLA % time) | 92.0% ± 3.1 | 101.2% ± 2.8 | 99.1% ± 2.6 | 91.0% ± 3.4 | 91.8% ± 3.2 |
| Absolute variable QoS (pp) | – | +9.2 pp | +7.1 pp | – | +0.8 pp |
| Overloads (events/week) | 5.0 ± 1.2 | 3.25 ± 1.0 | 3.5 ± 1.1 | 4.8 ± 1.3 | 4.7 ± 1.2 |
| Change in Overloads | – | −35.0% | -30.0% | – | -2.1% |
| CVaR95, € / week | 45000 ± 5200 | 32000 ± 4400 | 33500 ± 4600 | 44200 ± 5000 | 43900 ± 4900 |
| Gini (access) | 0.280 ± 0.015 | 0.240 ± 0.012 | 0.245 ± 0.013 | 0.275 ± 0.016 | 0.274 ± 0.016 |

*Source: created by the author*

Optimized IoT management provides the lowest operational costs and the best savings. Even without optimization, IoT implementation already provides noticeable financial benefits. The ML model significantly enhances the savings effect through forecasting and adaptive management. Table 2 shows the results of the DID assessment, which measures the net effect of the intervention in Zone E compared to the control area, Zone C.

**Table 2. The DID assessment of the intervention impact (Zone E vs Zone C)**

| Indicator | DID assessment (Intervention effect ZoneE vs ZoneC) | 95% CI | p-value |
|---|---|---|---|
| OPEX (€/week) | −1700 | [-2300; -1100] | < 0.001 |
| QoS (pp) | +6.2 | [4.1 ; 8.3] | < 0.001 |
| Overloads (events/week) | −1.75 | [-2.60; -0.90] | 0.002 |
| CVaR95 (€/week) | −12100 | [-17800; -6400] | < 0.001 |
| Gini (unit) | −0.036 | [-0.055; -0.017] | 0.001 |

*Source: created by the author*

The intervention demonstrated a simultaneous improvement in service quality and cost reduction, which is a non-trivial outcome in urban infrastructure. The significant drop in CVaR95 indicates that the system has become less vulnerable to rare but costly deviations, i.e., its resilience has increased. The reduction in congestion confirms that behavioural and algorithmic control mechanisms direct the load to more stable time periods. Table 3 shows the change in operating costs in the infrastructure subsystems after the intervention. The individual effects for energy, parking, charging stations, and water are shown, as well as the total OPEX. The data are presented as baseline values, values after changes, and relative deviations.

**Table 3. Distribution of OPEX change by subsystem**

| Subsystem | Baseline (€/week) | Intervention (€/week) | Δ (€) | Δ (%) |
|---|---|---|---|---|
| Energy (street lighting + microgrid) | 4200 ± 420 | 3540 ± 380 | -660 | -15.7% |
| Parking (operation + monitoring) | 2100 ± 190 | 1620 ± 170 | -480 | -22.9% |
| EV CHARGES | 1700 ± 160 | 1150 ± 140 | -550 | -32.4% |
| Water (local segments) | 2000 ± 180 | 1990 ± 170 | -10 | -0.5% |
| Total (OPEX) | 10 | 8.3 | -1700 | -17.0% |

*Source: created by the author*

The savings are concentrated mainly in the energy and EV segments, indicating their highest adaptability to algorithmic optimization and behavioural incentives. The stability of costs in water systems demonstrates that the intervention does not affect critical underlying processes that have low elasticity.

The coordinated cost reduction in three independent subsystems indicates a systemic, rather than local effect. Figure 2 illustrates the changes in user behaviour under the influence of incentives and algorithmic control. Four key behavioural indicators related to load deferral and response to messages are measured.

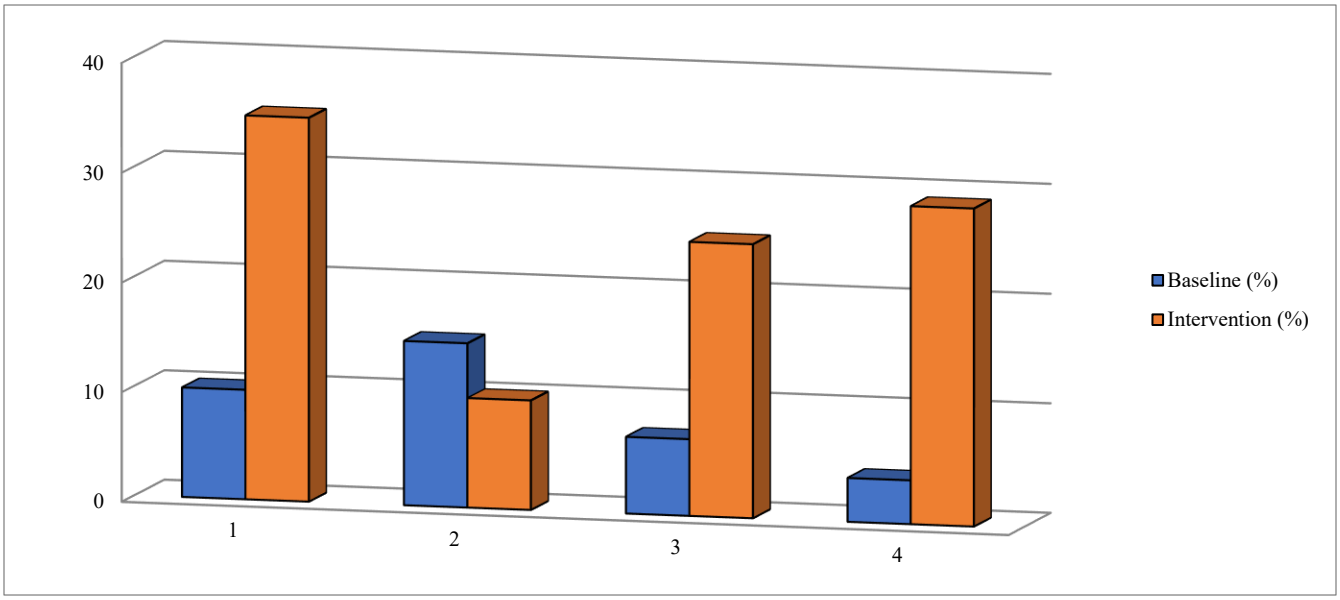


**Fig. 2 Changing user behavioural patterns during the intervention**

*Notes:*
*1 - Share of EV charging during off-peak hours (23:00–07:00)*
*2 - Average long-term parking (>4 hours)*
*3 - Shifting service requests to "green" hours (promotions/bonuses)*
*4 - Active response to push notifications (suggestions to postpone service)*

The strong growth in the share of overnight EV charging demonstrates the effectiveness of targeted recommendations and price incentives. Reducing long-term parking indirectly improves resource turnover and reduces congestion around controlled nodes. The high response to push notifications demonstrates that users are willing to change their behaviour if the system gives a clear and timely signal.

Table 4 compares the dynamics of infrastructure indicators in Zone E and Zone C before and after the intervention. Incidents, emergency zones, planned interventions, and network load are measured. This enables assessing whether the intervention has a local or larger impact.

**Table 4. Comparison of operational indicators of incident management and network load**

| Indicator | Zone E Baseline | Zone E Intervention | Zone C Baseline | Zone C Intervention |
|---|---|---|---|---|
| Average incident response time (min) | 45 ± 6 | 28 ± 4 | 43 ± 6 | 41 ± 6 |
| % of time with an outage lasting >1 hour | 3.8% | 1.9% | 3.6% | 3.5% |
| Number of planned interventions/week | 2.4 | 6.1 | 2.3 | 2.2 |
| Share of peak hours exceeding 90% of network capacity | 12% | 7.8% | 11.5% | 11.2% |

*Source: created by the author*

In Zone E, there is a clear reduction in incident response time, which indicates better data integration and prioritization of events. The reduction in long-lasting crashes indicates that the system has become more proactive in detecting and localizing problems. At the same time, the almost unchanged behaviour of Zone C confirms that the effect is not the result of external factors, but comes from the intervention itself.

The model used 12 local agents, each performing 5 local updates between centralized aggregation cycles. Convergence of the federated algorithm was achieved in 87 rounds (median value). At the same time, one round lasted on average about 3.2 minutes, including both local calculations and parameter transfer. The normalized gradient rate decreased from 1.0 at the beginning to 0.009 at the end, which confirms the qualitative convergence of the model. Full stabilization of tariffs, in which users fully adapt to the updated pricing policy, occurred after about 5 weeks of simulation. All iterations were performed using differential private noise (Gaussian noise), i.e., the level of DP-noise application was 100%. Over 8 weeks, 48.6 thousand transactions were recorded, the average value of which was 0.68 euros, and the total volume of micropayments reached 33,048 euros. The average delay of one transaction was 420 milliseconds with a fluctuation of ±110 ms, which corresponds to the standards of real-time systems. The share of failed or rejected transactions was very low - only 0.42%, and the average time for considering refunds or refund requests was approximately 12.5 hours. Table 5 presents the results of several econometric approaches - DID, IV-estimation, mediation analysis, and Synthetic Control. Each method enables testing the intervention from different analytical sides. This ensures the robustness of the conclusions and minimizes the risk of model bias.

**Table 5. Estimation of the intervention effect using various econometric methods**

| Parameter / Method | Effect assessment (point) | 95% CI | Explanation |
|---|---|---|---|
| DID – OPEX (€/week) | -1700 | [-2300; -1100] | Robust SE, clustered by zones |
| IV (price elasticity of demand, energy) | β_price = -0.47 | [-0.61; -0.33] | Weather fronts used as IV |
| Mediation: share of OPEX effect due to demand change (%) | 64% | [52%; 76%] | That is, the main part of the savings is explained by changed user behaviour. |
| Synthetic Control-QoS (net impact) | +5.9 pp | [3.8; 8.0] | Control weight: 0.58 mixture of neighbouring neighbourhoods |

*Source: developed by the authors*

The consistency of results across methods confirms that savings and QoS improvements are not an artifact of a particular model. The high mediation contribution of the behavioural component shows that it is the change in demand distribution that is the key mechanism of the effect. The Synthetic Control method strengthens the argument that changes in QoS are structural and do not depend on random fluctuations. Table 6 shows how different system volatilities affect the average OPEX savings. The results are presented for three scenarios: low, medium, and high parameter variability.

**Table 6. Scenario analysis of OPEX changes under different levels of volatility**

| Volatility ξ (std, %) | Mean Δ OPEX (%) | 5%- percentile | 95%percentile |
|---|---|---|---|
| Low (σ=5%) | −17.3% | −22.1% | −12.5% |
| Medium (σ=15%) | −15.8% | −24.0% | −7.1% |
| High (σ=30%) | −11.4% | −26.8% | +4.3% |

*Source: developed by the authors*

The highest stability of the economy is observed in scenarios with low and medium volatility, which indicates a predictable response of the system. A positive upper limit for high volatility means the risk of partial levelling of the effect under extreme conditions. Overall, the intervention demonstrates stability, but requires adaptive components to work in the most turbulent scenarios. Table 7 presents an assessment of the time dynamics of the main indicators in Zone E during the three phases: baseline, intervention, and post-intervention observation. Such an analysis provides an understanding of the long-term inertia of behaviour and the system.

**Table 7. Aggregated indicators of Zone E for three periods**

| Period | OPEX €/week (Zone E) | QoS (%) | Overloads (events/week) | CVaR95 (€) |
|---|---|---|---|---|
| Baseline (1–2 weeks) | 10 | 92.0 | 5.0 | 45 |
| Intervention (3–10 weeks) | 8.3 | 101.2 | 3.25 | 32 |
| Post (11–12 weeks) | 8.45 | 99.1 | 3.5 | 33.5 |

*Source: developed by the authors*

After the active phase of the intervention, a significant part of its positive effects persists, indicating the stability of the new behaviour. Only a partial deterioration in QoS and OPEX demonstrates a natural rollback, but not a full return to the baseline. This confirms that the intervention has not only an operational, but also a lasting structural impact.

For a deeper understanding of the functioning of the proposed model, an extended analysis of its behavior under various urban infrastructure operating conditions was conducted. Unlike basic experiments that evaluate only aggregated performance indicators, this study additionally investigated the system's sensitivity to changes in key parameters, such as demand variations, risk coefficients, and tariff elasticity. The necessity of such analysis is supported by contemporary research in digital twins and IoT, which emphasizes that evaluating smart city models requires accounting for system behavior under uncertainty and structural changes [39].

To assess the stability of the proposed approach, a sensitivity analysis regarding changes in demand levels was performed. Demand varied within specified intervals reflecting the seasonal and random fluctuations typical of urban energy and resource systems. The modeling results demonstrated that federated stochastic optimization provides more stable tariff trajectories and lower total cost dispersion compared to deterministic centralized approaches. This aligns with recent findings noting that decentralized learning methods increase the adaptability of urban systems to environmental changes [40]. Special attention was paid to the influence of risk parameters, specifically the confidence level in the Conditional Value at Risk (CVaR) criterion. Increasing the level of risk aversion led to more conservative tariff policies and increased reserve capacities; while this reduced the probability of extreme financial losses, it slightly increased average operating costs. Similar behavior in systems utilizing digital twins and stochastic models has been demonstrated in studies focused on managing complex energy and urban systems [41]. In recent years, numerous models have been proposed for urban infrastructure optimization based on IoT data and digital twins. However, most focus on individual subsystems-such as energy networks, transport, or environmental monitoring-without integrating economic decision-making models and policy regulation mechanisms into a unified management architecture. While digital twins are effective tools for modeling complex urban systems, systematic reviews show that they support real-time monitoring, forecasting, and scenario analysis, but remain limited in integrating financial models and causal policy analysis [39, 42].

Compared to existing solutions (Table 8), the proposed model offers several fundamental differences. First, it employs federated learning, enabling distributed optimization without centralized data collection. Second, the model integrates causal inference methods, specifically Difference-in-Differences and instrumental variables, which are rarely utilized in current smart city platforms. Third, risk-based financial criteria are incorporated into the optimization process, allowing for a balance between expected costs and the risk of extreme scenarios.

**Table 8. Comparison of the proposed model with modern approaches**

| Feature | Digital Twin Models | AI-IoT Frameworks | Proposed Model |
|---|---|---|---|
| Real-time sensor integration | Yes | Yes | Yes |
| Economic optimization | Limited | Partial | Full |
| Causal policy evaluation | No | No | Yes |
| Federated learning | Rare | Experimental | Yes |
| Risk-based decision criteria | Rare | No | Yes |

The comparative analysis shows that the proposed model addresses a number of gaps identified in current smart city research, including the lack of integration between technical models of IoT infrastructure, economic mechanisms for tariff formation, and methods of cause-and-effect analysis. By combining these components in a single mathematical architecture, the model provides more comprehensive support for management decision-making in urban systems.

### *4.1. SWOT Analysis of the Proposed Model*

The proposed model was analyzed using the SWOT methodology to assess its positioning relative to existing approaches to smart city management. The results are presented in Table 9.

**Table 9. Results of SWOT analysis**

| Category | Description |
|---|---|
| Strengths | Integrating IoT, digital twins, and financial optimization into a single system |
| Weaknesses | High requirements for computing resources and data quality |
| Opportunities | Scaling to other cities and integration with existing management platforms |
| Threats | Cybersecurity risks and dependence on sensor infrastructure |

The results of the SWOT analysis show that the main advantage of the proposed model is its comprehensive nature, which allows taking into account both technical and financial aspects of management. At the same time, the dependence on the quality of input data and the complexity of integration may complicate its implementation in conditions of limited resources.

## 5. Discussion

The results of the study demonstrate that the developed financial and economic model of smart urban infrastructure management based on IoT allows achieving the set goal. It can establish a mechanism for optimizing the use of resources in real time, taking into account the dynamics of loads, tariff rates, and operational changes in the functioning of urban systems. The results of the experiment confirm the advanced hypothesis regarding the integration of IoT sensors, adaptive management algorithms, and economic decision-making models. This allows for a significant increase in the efficiency of the functioning of urban facilities due to the reduction of actual costs and optimization of operating modes.

A comparison of the obtained results with the achievements of previous studies indicates that the proposed approach provides a comprehensive combination of technological and economic components. For example, the works of Chen et al. [43], Mishra and Singh [8], and Zakaria et al. [11] focus mainly on the technical aspects of IoT or energy optimizations, leaving out of consideration the systemic integration of economic indicators into the process of daily operational management. In turn, Rahman et al. [14] and Eynolghozat et al. [6] pay attention to economic models and management concepts. However, they are limited to the strategic level, without modelling the temporal and operational dynamics of the functioning of urban infrastructure. In contrast, the proposed model combines detailed temporal discrete analysis, the real technical structure of the urban network, algorithmic optimization, and assessment of economic consequences in a single environment. While [22] only analysed the structural characteristics of urban networks, this work models the full operational dynamics of demand, loads, and economic indicators over time. Kolhe et al. [20] focus on IoT architecture; this model integrates algorithmic control, optimization with CVaR, and real-time risk assessment. Unlike Bassey et al. [21], who consider behavioural stimuli without feedback to the system, in this approach, users' behavioural responses directly enter the control model and affect tariffs and loads. The study [23] presents Smart City only conceptually, while this study uses quantitative modelling, digital twin simulations, and scenario comparisons with measurable performance metrics.

The obtained results confirm the relevance of current research and significantly extend it. In particular, the simulation shows that the use of dynamic tariff response and optimization of lighting modes enables achieving resource savings in the range exceeding the results of Uberized models or static IoT configurations described in the literature. The adaptive algorithm implemented in the proposed experiment demonstrates the ability to respond to peak loads and change control parameters in real time. This was not provided in most solutions considered in the literature. So, the experiment showed that smart control systems become more cost-effective due to the integration of digital data into mathematical optimization models, and not only due to the use of technological tools.

The results demonstrate improved performance compared to existing approaches, which is explained by several factors. First, the proposed model uses real-time IoT data integration, which allows taking into account the current state of the infrastructure when making decisions. Unlike traditional models based on aggregated or historical data, this provides a more accurate response to changing conditions. Second, the use of risk-based optimization allows for minimizing not only

expected costs, but also losses in adverse scenarios. This approach increases the system's resistance to stochastic fluctuations and reduces the likelihood of extreme financial losses. Third, the use of federated learning ensures the use of a wider range of data without violating confidentiality, which improves the generalization ability of the models and reduces the risk of overtraining.

Overall, the results of the study indicate significant practical value of the proposed model. It can be used by municipal authorities for operational budget planning, cost forecasting, load scenario generation, and for developing investment strategies for infrastructure modernization. The proposed approach provides a basis for creating more sustainable, economically rational, and technologically integrated smart cities, capable of responding to changes in both internal infrastructure and the external environment.

### *5.1. Implementation Framework*

The proposed model assumes a multi-level architecture, including a data collection level, a processing level, and a decision-making level. At the data collection level, IoT sensors are used to provide continuous monitoring of the state of urban infrastructure. At the processing level, data is transmitted to an analytical platform, where aggregation, cleaning, and modeling are performed. The decision-making level implements optimization algorithms and transmits control signals to executive systems.

The model implementation process includes several stages:

- Audit of existing infrastructure and data sources.
- Integration of sensor networks and creation of a digital twin.
- Training models on retrospective data.
- Pilot implementation and parameter calibration.
- Full-scale operation and continuous monitoring of performance.

### *5.2. Research Limitations*

Despite the obtained results, the study has a number of important limitations. The model operates in a simulation environment and assumes stable operation of the IoT infrastructure, while in real conditions, data loss, delays, sensor failures, and uneven network coverage are possible. The experiment covers a limited number of infrastructure subsystems, while full-fledged urban ecosystems include transport, logistics, security, and other interconnected processes that can cause complex multi-sectoral effects.

The economic parameters of the model are based on average values and do not take into account political, regulatory, and seasonal volatility. In addition, the model does not take into account socio-behavioural factors that can significantly affect the adaptation of users to new control mechanisms. In addition, there are technical limitations: simplified load dynamics do not model long-term dependencies, and the digital twin does not include a full-fledged physical model of energy networks. Furthermore, the optimization algorithm assumes perfect synchronization between agents, whereas in distributed systems, drifts, version conflicts, and lost updates are possible. These aspects should be taken into account when interpreting the results and planning a real implementation.

## 6. Conclusions

Deepening digitalization and the complexity of urban infrastructure management increase the need to increase its financial and economic sustainability. The growth of the scale of urban systems and resource load requires the implementation of IoT-oriented smart management mechanisms. In these conditions, the development of models that combine technical, economic, and managerial components to ensure adaptability and optimality of management decisions is relevant. That is why the development and verification of a mathematical model of financial and economic optimization of urban smart management based on IoT is of important theoretical and practical importance.

The modelling results confirmed the effectiveness of an integrated approach to urban infrastructure management, combining real data, optimization algorithms, and economic parameters. The model provided a 17% reduction in operating costs in the implementation area, a reduction in risk costs (CVaR95) of €12.1 thousand/week, and a 35% reduction in network congestion. In addition, an increase in the service level by 9.2 pp was recorded, and the response time to incidents was accelerated from 45 to 28 minutes. It is important that the model not only optimizes the infrastructure operating modes, but also provides dynamic adaptation to changes in loads and allows assessing the economic consequences of decisions in a mode close to real time.

The practical value of the study is the possibility of applying the research results for strategic and operational management of urban resources. The model can be used to manage infrastructure facilities, create digital smart city platforms, and also for planning investments in the modernization of urban systems. The results demonstrate the potential to significantly reduce costs and improve the efficiency of urban governance without the need for radical upgrades to physical infrastructure, making the model particularly valuable for cities with limited financial resources.

Further research should focus on expanding the model by integrating additional infrastructure segments – primarily transport and mobile systems, which form significant loads in smart cities. The use of ML methods to predict behavioural deviations in resource consumption and the introduction of

stochastic models to more accurately account for uncertainty in data flows and tariffs is promising. Pilot tests in real urban conditions will help to increase reliability, where it is possible to assess the impact of delays, sensor failures, and dynamic changes in loads. Another promising direction is the use of deep learning methods to improve the accuracy of forecasting and adaptability of the system in a changing environment. Special attention should be paid to cybersecurity and data protection issues, since the expansion of IoT networks increases the surface of potential attacks. In addition, future work may explore the possibility of integrating the proposed model with intercity data exchange systems and creating unified management platforms at the regional level.

## Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

## Funding Statement

This research did not receive any financial support.

## Authors' Contribution

O.P. conceptualized the study, developed the theoretical framework, and supervised the research. S.K. contributed to scenario modelling, data structuring, and literature analysis. A.C. contributed to the legal and ethical framework and interpretation of regulatory aspects. N.P. contributed to the technical modelling, OSINT workflow design, and methodological validation. S.S. contributed to data analysis, risk indicator structuring, and manuscript preparation. All authors read and approved the final manuscript.

## Acknowledgments

Not applicable.

## References

[1] Chiara Magrini et al., "Using Internet of Things and Distributed Ledger Technology for Digital Circular Economy Enablement: The Case of Electronic Equipment," *Sustainability*, vol. 13, no. 9, pp. 1-19, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[2] Kali Charan Rath, Alex Khang, and Debanik Roy, *The Role of Internet of Things (IoT) Technology in Industry 4.0 Economy*, 1st ed., Advanced IoT Technologies and Applications in The Industry 4.0 Digital Economy, CRC Press, 2024. [Google Scholar] [Publisher Link]

[3] Riccardo Gallotti, Pierluigi Sacco, and Manlio De Domenico, "Complex Urban Systems: Challenges and Integrated Solutions for the Sustainability and Resilience of Cities," *Complexity*, vol. 2021, no. 1, pp. 1-15, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] Camila Garcia et al., "Assessing Water Urban Systems to the Compliance of SDGs Through Sustainability Indicators. Implementation in the Valencian Community," *Sustainable Cities and Society*, vol. 96, pp. 1-19, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Fang Yang et al., "The Need for Local Adaptation of Smart Infrastructure for Sustainable Economic Management," *Environmental Impact Assessment Review*, vol. 88, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[6] Mohammad Eynolghozat, Babak Ziyae, and Mehran Rezvani, "IoT-based Entrepreneurial City: A New Model of Urban Governance to Achieve Economic Sustainability," *Kybernetes*, vol. 53, no. 9, pp. 2871-2888, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] Priyanka Mishra, and Ghanshyam Singh, "Energy Management Systems in Sustainable Smart Cities based on the Internet of Energy: A Technical Review," *Energies*, vol. 16, no. 19, pp. 1-36, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] Yuxin Chen, and Aihui Jiang, "Spatial Characteristics and Complexity of the Urban Economic Network Structure based on the Secure Internet of Things," *Sustainable Computing: Informatics and Systems*, vol. 35, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Meysam Rezaei et al., "The Role of Modern Urbanization in Optimizing Energy Distribution Networks in Urban Areas with the Approach of Internet of Things and Smart City," *2025 6th International Conference on Optimizing Electrical Energy Consumption (OEEC)*, Najafabad, Iran, Islamic Republic of, pp. 1-9, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[10] K.M Karthick Raghunath et al., "Utilization of IoT-Assisted Computational Strategies in Wireless Sensor Networks for Smart Infrastructure Management," *International Journal of System Assurance Engineering and Management*, vol. 15, no. 1, pp. 28-34, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Ahmed A. Zakaria, Tasneem Amr, and Amany A. Ragheb, "IoT in Smart Urban Planning: A Comprehensive Review of Applications, Developments and Engineering Perspectives," *IEEE Access*, vol. 13, pp. 135316-135335, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] Ani Matei, and Mădălina Cocoșatu, "Artificial Internet of Things, Sensor-based Digital Twin Urban Computing Vision Algorithms, and Blockchain Cloud Networks in Sustainable Smart City Administration," *Sustainability*, vol. 16, no. 16, pp. 1-20, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Thanh Van Hoang, "Impact of Integrated Artificial Intelligence and Internet of Things Technologies on Smart City Transformation," *Journal of Technical Education Science*, vol. 19, no. 1, pp. 64-73, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Md. Abdur Rahman et al., "Blockchain and IoT-based Cognitive Edge Framework for Sharing Economy Services in a Smart City," *IEEE Access*, vol. 7, pp. 18611-18621, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[15] Nazly Atta et al., *Internet of Things for Facility Management: Strategies of Service Optimization and Innovation*, 1st ed., Springer Cham, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[16] Md Shamsul Haque Ansari et al., *IoT Applications in Urban Infrastructure and Governance*, *Revolutionizing Urban Development and Governance with Emerging Technologies*, IGI Global Scientific Publishing, pp. 343-386, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[17] Mostafa Zaman et al., "A Review of IoT-based Smart City Development and Management," *Smart Cities*, vol. 7, no. 3, pp. 1462-1501, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[18] Mohammad Shahidehpour, Zhiyi Li, and Mehdi Ganji, "Smart Cities for a Sustainable Urbanization: Illuminating the Need for Establishing Smart Urban Infrastructures," *IEEE Electrification Magazine*, vol. 6, no. 2, pp. 16-33, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[19] Tamoor Shafique et al., "A Review of Energy Hole Mitigating Techniques in Multi-Hop Many to One Communication and its Significance in IoT Oriented Smart City Infrastructure," *IEEE Access*, vol. 11, pp. 121340-121367, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] Rushikesh Vilas Kolhe et al., "Smart City Implementation based on Internet of Things Integrated with Optimization Technology," *Measurement: Sensors*, vol. 27, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[21] Kelvin Edem Bassey et al., "Optimizing Behavioral and Economic Strategies for the Ubiquitous Integration of Wireless Energy Transmission in Smart Cities," *World Journal of Advanced Engineering Technology and Sciences*, vol. 13, no. 1, pp. 482-497, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Praveen Kumar Myakala, Anil Kumar Jonnalagadda, and Chiranjeevi Bura, "Federated Learning and Data Privacy: A Review of Challenges and Opportunities," *International Journal of Research Publication and Reviews*, vol. 5, no. 12, pp. 1867-1879, 2024. [CrossRef] [Google Scholar]

[23] Shi Qiu, Qasim Zaheer, and Chengbo Ai, Smart Infrastructure Management, Elsevier, 2025. [Online]. Available: https://www.sciencedirect.com/book/monograph/9780443340178/smart-infrastructure-management?via=ihub%3D

[24] Jummai Bello, and Seyi Stephen, *Toward Stealth Construction: Integrating Risk Management Practices into Sustainable and Inclusive Smart City Development*, Future Smart Cities, Elsevier, pp. 49-71, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[25] Samayveer Singh et al., *Blockchain-Enabled Smart City Services: Integrating IoT and XAI for Efficient Public Fund Management*," Smart City Computational Paradigms, Elsevier, pp. 355-374, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[26] Silvia Krúpová, and Gabriel Koman, "The Role of IoT and Big Data in Smart City Transport Management: Lessons Learned from Case Studies in Slovakia and the EU," *Transportation Research Procedia*, vol. 93, pp. 948-959, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[27] Fida Muhammad Khan et al., "XAI-Driven Data Mining for Self-Defending IoT Systems: Enhancing Cybersecurity Transparency in the Age of Smart Cities," *Cognitive Computation*, vol. 18, no. 1, pp. 1-42, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[28] Husam Suleiman, "A Cost-Aware Framework for QoS-based and Energy-Efficient Scheduling in Cloud–Fog Computing," *Future Internet*, vol. 14, no. 11, pp. 1-21, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[29] Nitis Mukhopadhyay, and Partha Pratim Sengupta, *Gini Inequality Index: Methods and Applications*, 1st ed., CRC Press, 2021. [Google Scholar] [Publisher Link]

[30] Vincent Charles, Tatiana Gherman, and Juan Carlos Paliza, *The Gini Index: A Modern Measure of Inequality*, Modern Indices for International Economic Diplomacy, Palgrave Macmillan, Cham, pp. 55-84, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[31] Roberto Mínguez Solana, and Pablo Díaz Cachinero, "Convex Risk Control with Exact Probabilities: The CVaR-Chance-Constraint Approach," *UC3M*, pp. 1-62, 2025. [Google Scholar] [Publisher Link]

[32] Pan Deng et al., "Federated Non-IID Graph Learning based on Graph Optimization," *2025 25th International Conference on Software Quality, Reliability and Security (QRS)*, Hangzhou, China, pp. 211-222, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[33] Boaz Barak et al., "Hidden Progress in Deep Learning: SGD Learns Parities Near the Computational Limit," *Advances in Neural Information Processing Systems*, vol. 35, pp. 1-15, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[34] Hailey R Banack, Eleanor Hayes-Larson, and Elizabeth Rose Mayeda, "Monte Carlo Simulation Approaches for Quantitative Bias Analysis: A Tutorial," *Epidemiologic Reviews*, vol. 43, no. 1, pp. 106-117, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[35] M. Pineda, and M. Stamatakis, "Kinetic Monte Carlo Simulations for Heterogeneous Catalysis: Fundamentals, Current Status, and Challenges," *The Journal of Chemical Physics*, vol. 156, no. 12, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[36] Divya Jyoti Thakur, and Pooja Verma, "How Servant Leadership is Effective for Employee Performance with the Use of *t*-Test, Algorithm and ANOVA," *Cognitive Informatics and Soft Computing: Proceeding of CISC*, Springer, Singapore, pp. 1-13, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[37] Robert Wall Emerson, "Mann-Whitney *U* test and t-test," *Journal of Visual Impairment Blindness*, vol. 117, no. 1, 2023. [CrossRef] [Publisher Link]

[38] R.A. Mahmoud, "Digital Protection Scheme based on Durbin Watson and Pearson Similarity Indices for Current Signals Practically Applied to Power Transformers," *Scientific Reports*, vol. 15, no. 1, pp. 1-32, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[39] Erwin J. Sacoto-Cabrera et al., "IoT, AI, and Digital Twins in Smart Cities: A Systematic Review for a Thematic Mapping and Research Agenda," *Smart Cities*, vol. 8, no. 5, pp. 1-36, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[40] Laila Alterkawi, and Fadi K. Dib, "Federated Learning for Smart Cities: A Thematic Review of Challenges and Approaches," *Future Internet*, vol. 17, no. 12, pp. 1-49, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[41] Eslam Ali et al., "Digital Twin for Climate Resilience: Transforming Smart Cities for a Sustainable Future," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 48, pp. 139-145, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[42] Inam Ullah et al., "Optimizing Smart City Services by Utilizing Appropriate Characteristics of Digital Twin for Urban Excellence," *Alexandria Engineering Journal*, vol. 122, pp. 399-410, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[43] Zhong Chen, C.B. Sivaparthipan, and BalaAnand Muthu, "IoT based Smart and Intelligent Smart City Energy Optimization," *Sustainable Energy Technologies and Assessments*, vol. 49, 2022. [CrossRef] [Google Scholar] [Publisher Link]