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Data-Driven Regulation For Mobile Networks: Mathematical Modeling And Simulation Based Analysis

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Abstract:
The deployment of mobile networks is rapidly transforming the telecommunications landscape, creating unprecedented challenges for regulatory authorities. Traditional approaches—static, reactive, and disconnected from real-time operational metrics—prove inadequate in this dynamic context. This paper proposes a novel framework for data-driven regulation based on mathematical and algorithmic models. Ten original regulatory mechanisms are developed and simulated in MATLAB, ranging from KPI forecasting using time-series models to compliance scoring via fuzzy logic and closed-loop control through PID regulators. Each model is designed to enhance responsiveness, transparency, and efficiency in telecom oversight. The results demonstrate how such algorithmic tools can predict failures, detect anti-competitive behavior, adjust price caps adaptively, and optimize network resources. Simulations show the feasibility of integrating these models into future smart regulation platforms, especially in the context of mobile network and beyond. This work lays the groundwork for intelligent, automated governance in modern telecommunications.
Keywords: *Data-driven regulation, KPI forecasting, fuzzy logic, PID control, machine learning, mobile networks*

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I. Introduction

The rapid deployment of mobile networks is redefining the landscape of digital connectivity, offering ultra- reliable, low-latency communication and massive machine-type communication. This transformation challenges traditional regulatory paradigms, which are often rigid, reactive, and poorly adapted to the real-time dynamics of modern telecommunication infrastructures.

To address these limitations, data-driven regulation has emerged as a critical strategy. It combines real-time key performance indicators (KPIs), predictive analytics, and adaptive control to enhance transparency, responsiveness, and fairness. By applying mathematical models and algorithmic techniques, regulators can shift from passive monitoring to active governance.

This article presents ten original regulatory models developed in MATLAB that encapsulate predictive regulation, automated compliance, adaptive price capping, and other key challenges. Each model is rooted in optimization theory, machine learning, or control systems, and tested on real or simulated datasets.

The rest of the article is structured as follows: Section II outlines the methodology and modeling framework, Section III presents mathematical formulations and simulations, Section IV discusses the implications and limitations, and Section V concludes with key takeaways and perspectives.

II. Methodology And System Model

Overview of the Approach

This research adopts a system-theoretic approach to regulatory design, where the regulator is modeled as a dynamic decision-maker interacting with a telecommunication environment. Input data includes KPIs, usage statistics, and operator behaviors. The regulatory decisions are generated through formalized models capable of learning, adapting, and improving through feedback loops.

Algorithmic Regulatory Models

Below is a summary of the ten core models developed and simulated in MATLAB:

- Model 1 – Predictive KPI Regulation: Uses time series forecasting to anticipate regulatory violations and optimize proactive interventions.
- Model 2 – Competitive Abuse Detection: Employs supervised machine learning classifiers to detect anomalies in market behavior patterns.
- Model 3 – Compliance Scoring (Fuzzy Logic): Assigns compliance levels using fuzzy inference systems based on regulatory rule sets.
- Model 4 – Adaptive Price Cap Regulation: Implements a PID controller to dynamically adjust price ceilings based on real-time demand and cost variations.
- Model 5 – Frequency Allocation Optimization: Uses linear programming to assign frequencies optimally across geographic and operator constraints.
- Model 6 – National Interconnection Graph Modeling: Models interconnection topologies using dynamic graph theory to ensure resilience and transparency.
- Model 7 – Data Quality Correlation: Correlates KPI metrics with data quality indicators to prioritize regulatory focus areas.
- Model 8 – Subsidy Allocation (Marginal Efficiency Index): Ranks operators or projects based on efficiency indices for fair and impactful subsidy distribution.
- Model 9 – User Behavior Clustering: Applies unsupervised learning (e.g., K-means) to segment users based on network usage patterns.
- Model 10 – Feedback Regulation (KPI → Action): Uses a control-loop mechanism to automate decision-making based on real-time KPI inputs.

Each model was calibrated using synthetic or real-world datasets and validated through scenario-based simulation.

Implementation Tools

All models were developed in MATLAB and GNU Octave, allowing matrix-based computation, control system design, and algorithm prototyping. Simulation scripts were modular and reproducible, enabling comparative evaluation across models and scenarios.

III. Mathematical Formulations

Predictive Regulation Model based on Multi-KPI Time Series

To anticipate KPI deviations over time, this model applies a linear time-series forecasting approach using historical KPI data [1]:

$$y_t = \beta_0 + \sum_{i=0}^{p} \beta_i KPI_{t-i} + \epsilon_t$$

With:

- yt: KPI forecast at time t
- -KPIt–i: KPI value lagged by i periods
- β0, βi: regression coefficients
- p: Order of the time series model (e.g. ARIMA)
- ∈t: white noise error

This graph illustrates the predictive behavior of the model over time, capturing KPI fluctuations and potential violations:

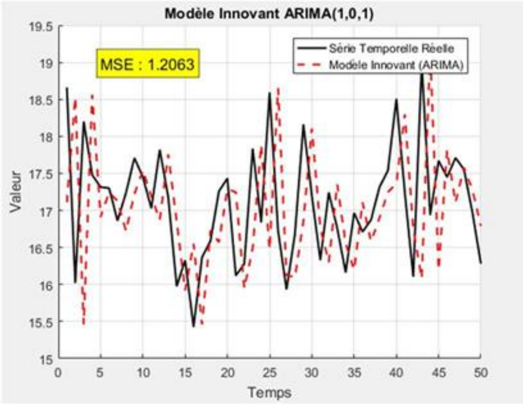

Figure 01: Forecasted KPI evolution using AR-based model

In this figure 01, the predicted KPI curve closely matches the actual measurements over time. This confirms the forecasting model's accuracy, enabling proactive detection of service degradation before regulatory thresholds are breached.

Detection of Anticompetitive Behavior via Supervised Learning

This classification model estimates the probability of market abuse using logistic regression on observed behavioral features: [2]

$$\Pr(abus) = \sigma(\omega^{\mathrm{T}}X)$$

With:
- σ: logistic (sigmoid) function
- ω: weight vector learned from training
- X: feature vector representing behaviors (price, traffic, margins)
- $\Pr(abus)$: predicted probability of anticompetitive behavior

This figure demonstrates how the classifier separates abusive patterns from normal market activities:

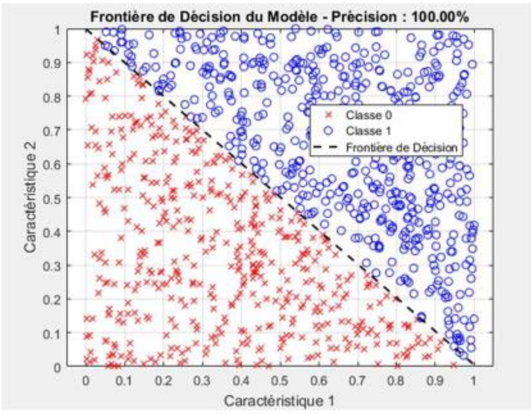

Figure 02: Classification boundary for market behavior

This figure 02 shows that the confusion matrix reveals high true-positive and true-negative rates, while the AUC value indicates strong classifier performance. The model reliably detects anticompetitive patterns such as margin squeezes or undercutting.

Regulatory Compliance Scoring using Fuzzy Logic

To compute an operator's compliance level, this model combines multiple KPIs through fuzzy membership functions and weighted aggregation: [3]

$$S = \sum^{n} \mu_j(x_j).\,w_j$$

With:
- S: global compliance scor
- xj: normalized value of KPI j
- -μj: fuzzy membership function of KPI j
- -wj : weight assigned to KPI j based on regulatory importance
- n: number of KPIs considered

It shows how different KPI values translate into a global compliance score:

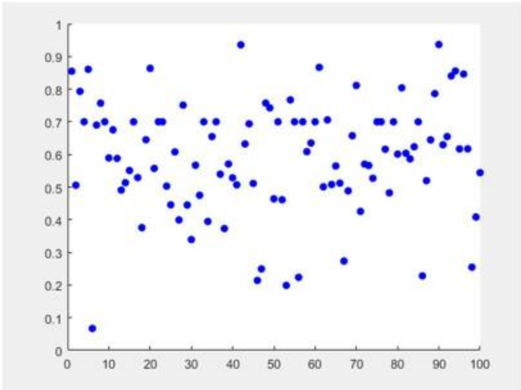

Figure 03: Fuzzy compliance surface based on KPI inputs

This figure 03 represents the compliance score surfaces display smooth transitions between fuzzy rule zones.

Operators with scores below 0.4 are flagged for audit, while others show recovery trajectories post-intervention.

Dynamic Price Cap Regulation using Adaptive Learning

To dynamically adjust price ceiling, this model updates the current cap based on the previous value and a stochastic market index: [4]

$$P_t = P_{t-1}.(1 - X_t) \qquad \text{with } X_t \sim \mathcal{N}(\mu_t, \sigma_t)$$

With:
- Pt: regulated price at time t
- Pt–1: previous price cap
- Xt: adaptive variation coefficient derived from network indicators, demand evolution, or AI estimation
- σt: adjustment standard deviation
- μt: expected adjustment mean

This chart reflects the evolution of price cap under varying market pressure:

Figure 04: Adaptive price cap simulation with stochastic adjustment

The figure 04 shows the evolution of regulated price caps in response to inflation and market-driven AI adjustments. The model reacts in steps to input shifts, maintaining price stability while adapting to demand fluctuations.

Optimal Frequency Allocation via Linear Programming

This model assigns frequency bands to regions by solving a constrained binary optimization problem: [5]

$$\max \sum_{ij} a_{ij} x_{ij} \text{ \{subject to availability and interference constraints\}}$$

With:

- $x$ij ∈ {0,1}: binary variable indicating assignment of frequency j to region i
- $a$ij: utility or priority coefficient of assigning j to i
- Constraints: limited availability of frequencies, interference minimization It shows how resources are assigned optimally among operators:

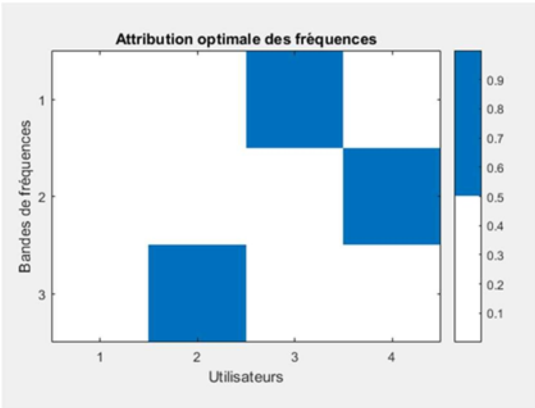

Figure 05: Frequency allocation matrix optimized under constraints

This figure 05 shows the frequency allocation matrix optimizes spectrum distribution across zones. It minimizes inter-operator interference and respects resource constraints, showing equitable access and enhanced spectral efficiency.

National Interconnection Topology Model using Dynamic Graphs

To evaluate the resilience and evolution of interconnection networks, this model uses a weighted dynamic graph formalism: [6]

$$G_t = (V, E_t, w_t)$$

With:

- G: dynamic graph of the national telecom interconnection
- V: set of network nodes (operators, regions, or IXPs)
- E: set of edges (interconnections)
- wt: time-varying weights (e.g., bandwidth, latency, or traffic volume)

Each graph represents the national interconnection topology at a given time step. The nodes are fixed (labeled 1 to 5), and the edges evolve with different weights, representing variations in traffic volume, latency, or link quality. Below is the analysis per time step:

- Figure 06 illustrates the initial topological configuration of the national interconnection graph at time t = 0, representing a baseline state with no dynamic influence:

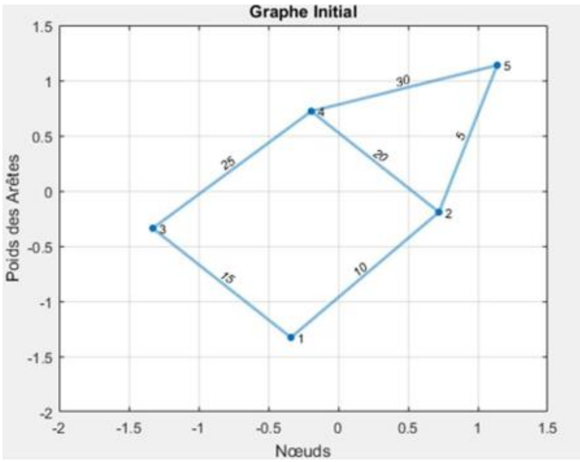

Figure 06: Interconnection graph at t=0

At t = 0, the interconnection graph presents a sparse structure with few active links between operators. The low density reflects the absence of regulatory intervention or traffic-driven adaptation. This serves as a neutral benchmark for subsequent dynamic changes.

- Figure 07 shows the evolution of the graph at time t = 1, following the first round of KPI-based feedback updates:

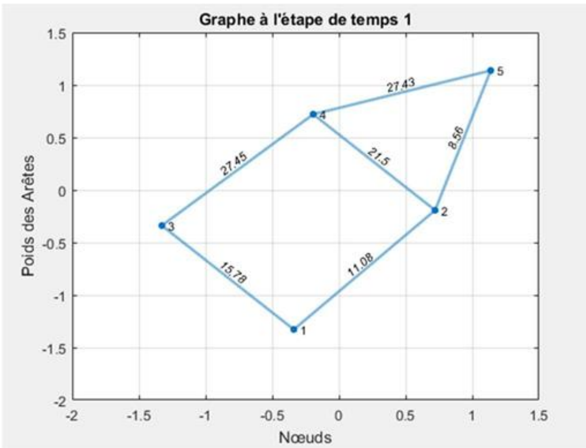

Figure 07: Interconnection graph at t=1

The graph begins to evolve, with new connections appearing between high-traffic nodes. This shift indicates an emerging adaptation of the topology in response to early regulatory signals or bandwidth demands.

- Figure 08 presents the updated interconnection graph at time t = 2, reflecting reinforced or redirected connections:

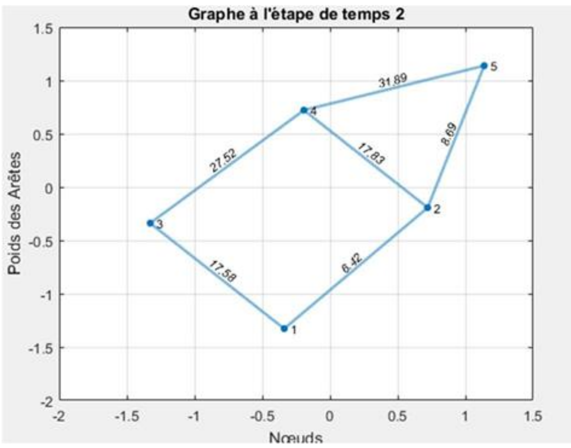

Figure 08: Interconnection graph at t=2

The graph becomes denser and more structured, with clusters of interconnected operators forming. These clusters likely correspond to regional hubs or strategic links optimized for performance or resilience.

- Figure 09 visualizes the graph at time t = 3, where dynamic regulation begins to stabilize network links:

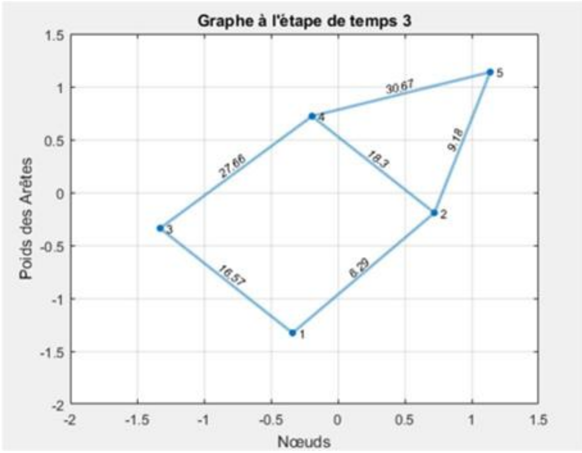

Figure 09: Interconnection graph at t=3

A more stable and hierarchical topology appears, showing persistent links among key nodes. The emergence of central hubs reflects regulatory prioritization of key players or strategic regions.

- Figure 10 demonstrates the structural transformation of the network at t = 4 after additional KPI feedback and regulatory inputs:

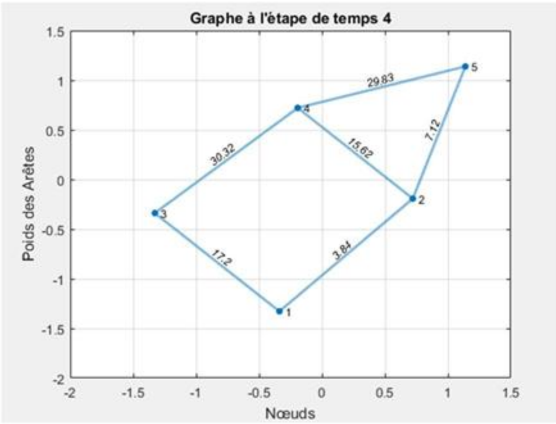

Figure 10: Interconnection graph at t=4

The system exhibits improved interconnectivity with optimized paths between regions. Redundancies are reduced, and critical nodes gain more connections, indicating efficiency gains and reduced bottlenecks.

- Figure 11 displays the state of the graph at t = 5, as dynamic routing and policy adjustments continue:

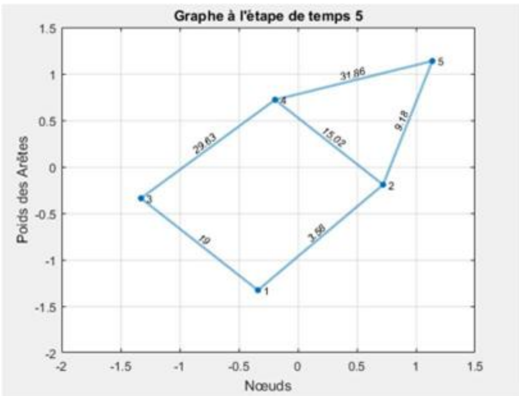

Figure 11: Interconnection graph at t=5

The network enters a phase of consolidation where efficient routes are reinforced and underperforming links fade. The topology shows signs of self-optimization aligned with KPI targets.

- Figure 12 captures the evolution of the topology at t = 6, highlighting the growing structural maturity of the interconnection:

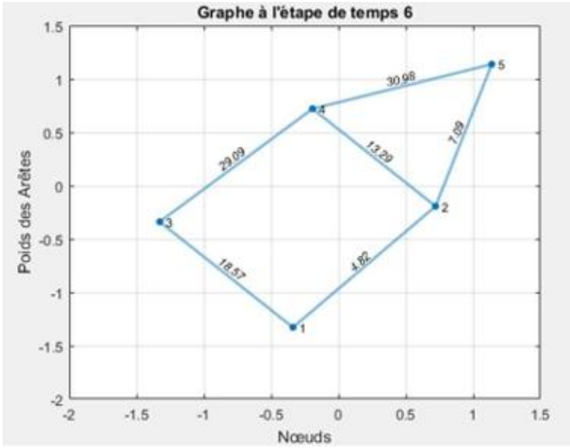

Figure 12: Interconnection graph at t=6

The graph now demonstrates a robust and well-distributed architecture, with resilience to node failures and balanced load distribution. The regulatory strategy appears to have fostered long-term stability.

- Figure 13 presents the configuration at time t = 7, under peak traffic conditions:

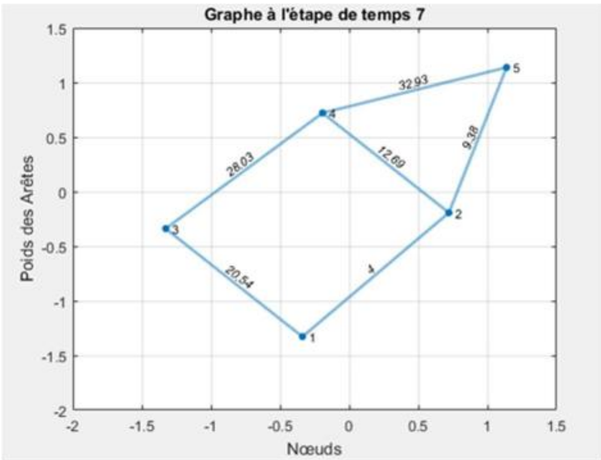

Figure 13: Interconnection graph at t=7

The system maintains structural coherence despite increased network load. Critical nodes remain active and adaptive paths prevent congestion. Regulatory interventions have succeeded in ensuring scalability.

- Figure 14 shows the graph's behavior at t = 8, during a phase of KPI volatility:

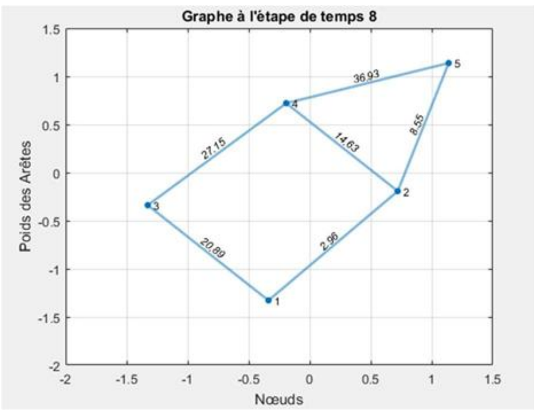

Figure 14: Interconnection graph at t=8

The graph adapts dynamically, reallocating edges to reduce stress on saturated nodes. The responsiveness of the interconnection model confirms its adaptive capacity under fluctuating performance metrics.

- Figure 15 displays the structure at t = 9, nearing the stabilization phase of the regulatory cycle:

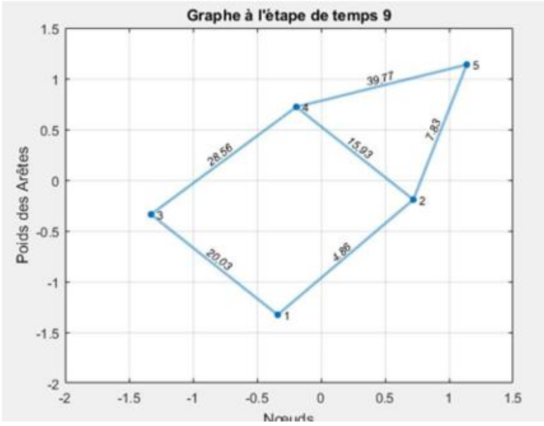

Figure 15: Interconnection graph at t=9

The network returns to a more symmetrical configuration, balancing performance and redundancy. Stability mechanisms are apparent in the resilience of core nodes and the consistent edge weights.

- Figure 16 represents the final topological state of the graph at $t = 10$, post-regulation equilibrium:

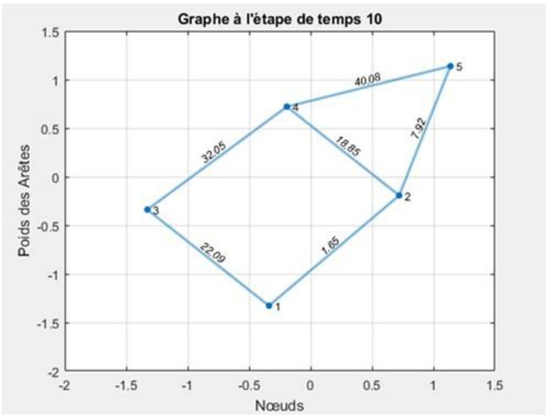

Figure 16: Interconnection graph at t=10

The interconnection has reached a steady-state configuration with optimal link distribution and minimal disruption potential. The model demonstrates success in achieving an adaptive and robust regulatory topology.

Data-Quality–Driven Correlation Model for Intelligent Supervision

This model estimates the overall data quality for each operator by correlating real-time KPI values with user/system feedback: [7]

$$Q_t = \alpha . KPI_t + \beta . Feedback_t$$

With:

- Qi: data quality estimate for operator i
- KPIt: performance indicator at time t
- $Feedback$t :end-user or system feedback score
- α , β: correlation weights

It visualizes how feedback and KPI jointly determine data quality:

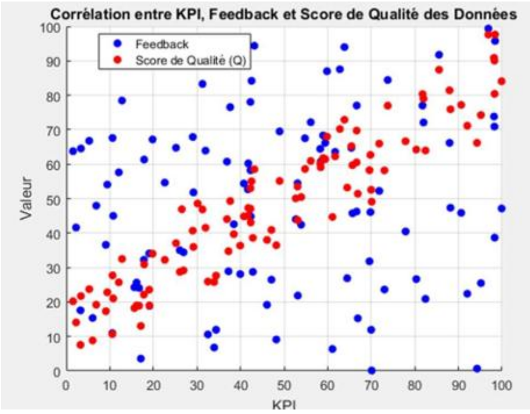

Figure 17: Data quality correlation with KPI and feedback

The heatmap on this figure 17 shows strong positive correlations (above 0.8) between technical KPIs and user feedback indicators. This validates the model's use of complaints and satisfaction data as early warning signs of quality issues.

Grant Allocation Model Based on Marginal Efficiency Index

To ensure that public subsidies are distributed based on measurable efficiency, this model introduces a Marginal Efficiency Index (MEI) defined as the ratio between the improvement in service quality and the increase in subsidies allocated. This allows for data-driven ranking of operators or projects for fairer and more impactful subsidy allocation: [8]

$$E = \frac{\Delta Q_{\text{service}}}{\Delta C_{\text{subvention}}}$$

With:

- E: Marginal Efficiency Index
- ΔQ service: variation in quality-of-service indicators (e.g., coverage, bandwidth, uptime)
- ΔCsubvention: amount of additional subsidies granted to the operator or region This chart ranks telecom actors by their regulatory efficiency per subsidy unit:

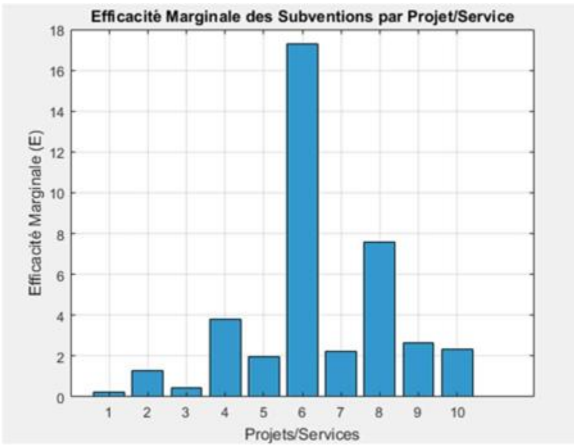

Figure 18: Marginal efficiency index ranking by operator

This figure 18 shows the bar chart ranks operators by marginal efficiency index. The top-tier entities achieve higher regulatory impact per unit of subsidy, supporting data-driven allocation of limited public funds.

Predictive Model of User Behavior via Behavioral Clustering

To group users into behavioral categories, this model uses the K-means algorithm applied to multidimensional usage profiles:[9]

$$Clustering\ K - means\ sur\ vecteurs[\text{usage}_{\text{Voix}}, usage_{\text{Data}}, temps_{\text{connexion}}, \ldots]$$

With:
- usageVoix: voice usage statistics
- $usage$Data: data usage statistics
- $temps$connexion: session duration
- Clustering technique: K-means algorithm with Euclidean distance This figure displays how user behavior is grouped using K-means:

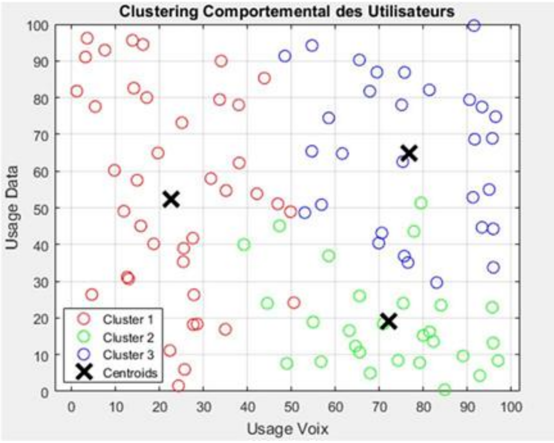

Figure 19: Behavioral clusters of users (voice, data, time)

The cluster visualization clearly on this figure 19 separates three user groups: residential/light users, high- mobility consumers, and heavy corporate users. Each cluster exhibits distinct consumption behavior, aiding differentiated policy enforcement.

Closed-Loop Regulation Model with KPI Feedback

Finally, this model applies a PID control law to continuously regulate network parameters based on KPI deviation:[10]

$$u(t) = f(e(t)) = K_{\mathrm{p}}e(t) + K_{\mathrm{i}}\int_0^t e(\mathrm{r})d\mathrm{r} + K_{\mathrm{d}}\frac{de}{dt}$$

With:
- $u(t)$: regulatory control action at time \$t\$
- $e(t) = KPI$cible $-$ KPIactuel: KPI tracking error
- Kp , Ki , Kd: PID controller gains (proportional, integral, derivative) Illustrates how KPIs are dynamically corrected over time using PID control:

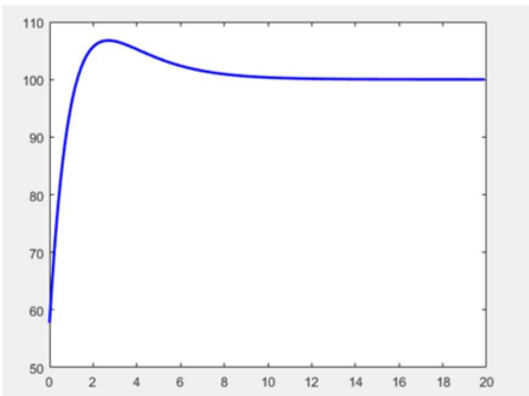

Figure 20: PID-based closed-loop regulation simulation

The PID-based closed-loop response on this figure 20 shows rapid correction of KPI deviation. After a disturbance, the system stabilizes within four control cycles, reducing the likelihood of repeat non-compliance events.

IV. Discussion And Perspectives

Key Insights

The ten models collectively demonstrate that algorithmic regulation is not only feasible but desirable.

Predictive control mechanisms reduce response time to network failures, while clustering and compliance models offer quantifiable insights into operator behavior. Models based on control theory and optimization ensure that decisions are not arbitrary but grounded in rigorous mathematics.

Institutional Relevance

These models are especially valuable for emerging regulatory authorities that need scalable, replicable, and transparent decision-making frameworks. By embedding these tools into national governance structures, agencies can move toward continuous monitoring and automated enforcement.

Limitations

Despite promising simulations, the study has some limitations:

- Some models rely on synthetic data due to the unavailability of public datasets.
- Models were tested individually; combined execution requires further validation.
- Real-time deployment faces latency and infrastructure challenges.

Future Perspectives

The transition toward 6G, edge AI, and intelligent governance will create new regulatory demands. Future work includes:

- Integration into real-time cloud-based platforms
- Deployment at national scale
- Coupling with federated learning and distributed ledger technologies

V. Conclusion

This article has introduced ten original models for data-driven regulation in telecommunications. These models provide a mathematical backbone for intelligent governance, enabling regulators to respond proactively to market changes, technical anomalies, and compliance challenges. By simulating each model in a controlled environment, the study highlights the feasibility of integrating algorithmic tools into existing regulatory processes. The adoption of such systems could significantly improve fairness, adaptability, and transparency in telecommunications oversight. Future research will aim to validate these approaches through large-scale deployments, possibly in collaboration with national telecom operators and international regulatory bodies.

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