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Scenario-Based Optimization of Public Service Workflows Using Control Theory and P-graph Methodology

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Administrative workflows in public services, such as university enrolment are increasingly recognized as complex systems characterized by nonlinear dynamics, interdependencies, and variable operational constraints. These characteristics often lead to inefficiencies in resource allocation and compromise process sustainability. This study develops a novel control-theoretic optimization framework that integrates feedback, adaptive, and predictive control strategies with the P-graph methodology to address these challenges. The proposed approach models enrollment workflows using system dynamics and P-graph-based network optimization, enabling structured representation, real-time control, and scenario-based decision-making. To assess sustainability and efficiency, the model simulates varying scenarios of student demand, digital transformation levels, and administrative capacity. Key performance indicators (KPIs) such as resource utilization, delay reduction, and process flexibility are used to evaluate the comparative effectiveness of Model Predictive Control (MPC), discrete-event control, and feedback control strategies. Results show that optimized scenarios achieved a 50 % reduction in CO_2 emissions and over 2 h reduction in average processing time, significantly improving sustainability. This research uniquely applies control-theoretic methods to public administration and extends the P-graph methodology beyond industrial domains. The outcome is a scalable decision-support framework for policymakers aiming to enhance the resilience and sustainability of administrative service processes under dynamic conditions.

1. Introduction

Nowadays, the sustainability of administrative processes has become a strategic issue for public and private organisations, as they need to operate not only in an efficient and customer-oriented way, but also in an environmentally and socially responsible way (Balassa Eisinger and Buics, 2024). This means, among other things, reducing unnecessary resource and bureaucratic demands, reducing workloads to avoid burnout, and integrating environmental considerations into process design. A further challenge is that administrative processes are often subject to fluctuating workloads (e.g. overloaded during peak periods), consist of many discrete steps - between which a smooth transition must be ensured to avoid errors and congestion - and involve complex decision structures (covering continuous resource management and discrete events). To address these challenges, modern decision support methods are needed. Despite advances in process optimization and control, few studies have examined how nonlinear control theory can be integrated with combinatorial process synthesis (P-Graph) to manage sustainability in public service workflows. This study aims to address this gap by utilizing P-Graph methodology and control theory approaches together. Control theory tools provide a promising solution by dynamically responding to process state changes through closed-loop feedback. For example, automated manufacturing can reduce energy consumption and environmental pressures (Henao-Hernández et al., 2019), and supply chains can increase dynamic planning capability and resilience (Ivanov et al., 2018). Advanced control techniques also contribute to the alignment of economic, environmental and social goals in production planning (May et al., 2023), while deep learning-based forecasting enables more flexible resource allocation in cloud services (Rossi et al., 2025). Advances in control theory have enabled efficient control of nonlinear, multivariate processes (Qin and Badgwell, 2003), and nowadays the incorporation of direct

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economic objective functions can also improve performance (Amrit et al., 2013). Discrete event control focuses on decisions that occur between two process steps, ensuring the correct sequence of steps and error-free operation. Non-blocking optimal control can be implemented in very complex systems (Wonham et al., 2018). A new approach to system stabilization has also been developed: by combining Lyapunov stability and max-plus algebra, Konigsberg (2015) has developed a method to stabilize the state of discrete event systems over the long term (Konigsberg, 2015). To integrate continuous and discrete decision making, hybrid management approaches are used that simultaneously address resource allocation (continuous) and task scheduling (discrete) decisions. Moreover, addressing sustainability challenges requires new approaches in complex, multi-dimensional systems, and model-predictive and hierarchical governance plays a key role in energy and emissions management (Daoutidis et al., 2016). Implementing sustainability management systems requires not only technical but also organisational changes. A case study shows that the integration of traditional and sustainability control systems helps embed sustainability (Beusch et al., 2022), while research shows that control systems are only effective when formal design is aligned with users' values and practices (Johnstone, 2019). New technologies also help to promote sustainable operations: for example, in data centres, significant energy savings can be achieved by dynamically shifting workloads and using local energy sources, while smart methods (e.g. fuzzy logic, neural networks) are effective in nonlinear systems (Lee, 2023). The P-graph methodology was originally designed for network synthesis in chemical processes, but in recent years it has been shown to be effective for sustainability and administrative processes as well. Tick (2007) found that P-graph-based workflow modeling is a preferred alternative to traditional modeling methods because its structural axioms guarantee the correctness of the models (Tick, 2007).A new technique allows generating and evaluating implicit decision rules from expert rankings using the P-graph, which is useful in complex, multi-criteria decision situations where decision makers' preferences are not clear (Low et al., 2020). The P-graph has also been proven in the design of sustainable industrial technologies: it has been used to optimize a biomass supply network to meet EU emission limits at minimal cost (Kodba et al., 2024). Migo-Sumagang et al. (2024) combined the P-graph with Monte Carlo simulation to investigate the robustness of portfolios of negative-emission technologies, finding the optimal balance between cost and risk; a recent review shows that the method is also effective in the design of negative-emission technologies and carbon management networks (Migo-Sumagang et al., 2022). In a university case study, P-graph analysis helped balance administrative and research capacities (Aviso et al., 2019), highlighting critical system resources and linkages. The aim of this study is to present a sustainability-oriented decision support framework, integrating P-graph methodology and management theory tools, which can be applied to optimise public administration processes and contribute to a more resilient, flexible and environmentally aware public service operation. The aim of the study is to develop a control-theoretic-based optimisation framework that can improve the efficiency, sustainability and resilience of administrative processes, in particular university enrolment. The research investigates how feedback, predictive and discrete event-driven management strategies can be integrated with the P-graph methodology and how this integration can be applied under different scenarios, such as different student enrolment, digitisation levels or capacity workloads. The novelty lies in the extension of the application of control theory tools to public administration processes and in the use of the P-graph methodology as a structured decision support tool in the public services sector, going beyond its industrial applications. By comparing the effectiveness of different control strategies with quantitative indicators such as resource utilisation, waiting time reduction, process flexibility, the optimal approach to promote responsive and sustainable public administration will be identified.

2. Materials and Methods

This study investigates the university enrollment process as a representative administrative service that is structured, resource-constrained, and exposed to demand fluctuations. The process consists of steps from the intake of applications to eligibility verification, document handling, decision-making, and final registration. The steps exhibit nonlinear behavior due to bottlenecks, task interdependencies, and varying available resources such that the process is an ideal candidate for control-based modeling and scenario analysis. The case study was replicated in manual-intensive and digitized versions to examine process effectiveness under different technology and organizational setups. Five process scenarios were developed to represent realistic variations in digital maturity and process control. The manual-intensive process without structured optimization was used as the baseline scenario. The other scenarios were the fully digital process with fixed structure and no control (Digital Static), the digital workflow with reactive control adjustments based on real-time data (Feedback Control), the predictive control strategy using historical demand trends (MPC), and the event-driven workflow transitions managed by system triggers (Discrete Event Control). Each scenario was analyzed under typical and peak student enrollment conditions to examine how the process performance (for example delay, resource utilization, throughput) responds to varying operational pressures and control strategies. The administrative operations were modelled as dynamic systems where the inputs (applications), the outputs (e.g. completed enrollments), and internal states (queue sizes, resource state) evolve over time.

- Feedback Control: Controls task scheduling and staff in relation to queue length or system burden.
- Model Predictive Control (MPC): Forecasts peak demand based on historical data and pre-allocates resources.
- Discrete-Event Control: Uses process triggers (application load thresholds) to direct tasks or invoke fallback processes.

The control structure enables scenario testing under various conditions of uncertainty, latency, and availability of resources. The P-Graph model was constructed using the P-Graph Studio software, encoding tasks as O-type nodes (operating units) and resources as M-type nodes (material unit. Logical combinatorics were applied to generate optimal process structures using the maximal structure generation and solution structure generation algorithms (Tick, 2007). For control implementation, MPC was applied using linear prediction models with a rolling horizon strategy. Feedback control relied on real-time delay data to reallocate resources dynamically, while discrete-event control was simulated to evaluate system behavior under stochastic arrivals. P-graph was used to determine all potential workflow structures under input-output constraints, to optimize routing and resource allocation for minimum redundancy and delay, and to support control strategy development by simulating how structural configurations respond to control interventions. By combining P-graph with control-theoretic methods, the research modeled both the structural and dynamic aspects of the enrollment workflow. The scenarios were compared on qualitative and quantitative parameters such as average processing time per request, system throughput and queue delay, resource utilization at peak and regular loads, process flexibility (the ability to adapt to changing demands), control effectiveness (the stability and responsiveness of the process), and sustainability factors like energy intensity and workload allocation. Each control strategy was compared on the basis of whether it could mitigate overload, improve resource utilization optimization, and raise process resilience and robustness. The P-graph was employed to represent structural adaptation in all cases and to quantify benefits gained through reconfiguration.

3. Calculation

To enable comparison across control strategies, the university admissions process was modelled as a discrete-time dynamic system, with administrative tasks being executed in sequence with measurable resource consumption and time delays. Key assumptions include that the process handles a finite volume of applications (A), which are processed in discrete rounds (batches or single events); resources (R) (staff, systems, etc.) are pooled across tasks and they are constrained by their availability; tasks exhibit nonlinear delay characteristics under heavy load, such as queue time increases disproportionately with application volume; and control methods aim to minimize overall delay and balance the utilization of resources.
The formula used for the calculations delay and queueing is:

$$D_j = \sum_{i=1}^{n} (T_i + \frac{Q_i(t)}{R_i} * T_i) \tag{1}$$

The formula used for the calculation average system delay is:

$$D_{av} = \frac{1}{A} \sum_{i=1}^{A} D_j \tag{2}$$

where D_j refers to Total process delay per application; T_i: Average processing time for task i; $Q_i(t)$: Queue length for task i at time t following a Poisson distribution to reflect real-world demand fluctuations; R_i: Number of resources assigned to task I; D_{av}: Average process delay per application; A: Number of applications to process. Each control strategy (s) is evaluated against the baseline (b) in terms of delay reduction:

$$PI_s = \frac{D_b}{D_s} \tag{3}$$

where PI refers to Performance Index relative to baseline and S refers to the scenario index; $PI_s>1$ indicates a performance improvement. To reflect the ability of a process to adapt under control strategies, a flexibility score is defined based on the number of feasible reconfigurations (N_f) are generated by the P-graph under each scenario:

$$F_s = \frac{N_f}{N_{f,max}} \tag{4}$$

where F refers to Flexibility score of process configuration; N_f: Number of feasible reconfigurations; $N_{f,max}$ is the total number of feasible process variants for the most flexible (hybrid) scenario. The formula used for the calculation resource utilization (U_i) for task i under scenario s:

$$U_i = \frac{Total\ active\ time}{Total\ available\ time} = \frac{A * T_i}{T_{max} * R_i} \tag{5}$$

The formulas used for the calculations are for the energy consumption per task:

$$E_i = P_i * T_i * n_i \tag{6}$$

$$E_{total} = \sum_{i=1}^{N} E_i \tag{7}$$

where E_i: Energy consumption of task i (kWh); P_i: Power consumption of device or activity used in task i (kW); T_{max}: Maximum processing time allowed for task i (h); n_i: Number of instances of task i in the process; N: number of tasks in the scenario process. The formula used for the calculations are for CO_2 emission is:

$$CO_{2_{total}} = \gamma * E_{total} \tag{8}$$

where γ: Grid-specific emission factor (0.366 kg CO_2/kWh); E_{total}: Total energy consumed by the process (kWh). These indicators provide a basis for multi-criteria evaluation of each control strategy's impact on process sustainability and efficiency.
In this control-theoretic framework, manipulated variables include staffing levels, resource assignments, and scheduling rules. Controlled variables are average processing time, queue length, and energy usage.

4. Results

In Table 1 we can see the five process scenarios simulated under both regular and peak-load conditions to evaluate performance in terms of average delay (D), resource utilization (U), and flexibility (F), Energy intensity and CO_2 emission.

Table 1: Comparative Performance of Control Strategies

Scenario	Avg. Delay (D)	PI (vs. Baseline)	Flexibility Score (F)	Max Utilization (U)	Energy Use (kWh/1000 cases)	CO_2 Emissions (kg)
Baseline (Manual)	4.5 h	1.00	0.30	0.75	182.00	66.61
Digital Static	3.2 h	1.41	0.40	0.82	128.42	47.00
Digital + Feedback Control	2.6 h	1.73	0.65	0.90	97.27	35.60
Digital + MPC	2.2 h	2.05	0.70	0.88	103.90	38.02
Digital + Discrete-Event	2.1 h	2.14	0.78	0.92	89.58	32.78

The scenario-based analysis showed that using control theory enhances administrative process performance in a number of ways. Compared to the manual baseline, digitally enabled scenarios in every scenario reduced processing delay, increased resource utilization, and improved structural flexibility. Of the control strategies employed, Digital + Discrete-Event Control performed best overall with the lowest average delay (2.1 h), highest flexibility score (0.78), and maximum utilization (92 %). For sustainability purposes, control scenarios that were control-driven exhibited large reductions in energy intensity and CO_2 emissions. The Digital+Feedback Control and MPC scenarios exhibited balanced performance improvements with environmental benefits, while the Discrete-Event Control scenario exhibited lowest emissions (32.78 kg CO_2 per 1,000 applications) and highest energy efficiency (0.09 kWh/application). These results validate the effectiveness of combining control-theoretic methods and P-graph-based structural optimization in enhancing administrative process operational and environmental performance. By using P-graph, all the scenarios were compared based on the number of alternative process structures. The hybrid and event-driven scenarios generated the maximum alternative structures because they were the most flexible. Flexibility score (F) was directly proportional to less delay and improved responsiveness, and therefore structural flexibility directly impacts control effectiveness. P-graph also found inefficiencies in the baseline case such as redundant routing and resource bottlenecks, and made it easy to generate optimized variants reducing queue accumulation under heavy load. Utilization analysis showed that the baseline process was suffering from underutilization during early stages as well as overload in bottleneck activities during peak periods. In comparison, control methods had more equal use of resources. From the results feedback control dynamically allocated resources based on backlog levels, MPC planned ahead based on expected load, smoothing out peak demand periods, while discrete-event control outperformed both of them by triggering structural adaptations and task switches based on real-time system status. These approaches ensured smoother queue dynamics and prevented overload at the peaks of enrollment. As we can see on Figure 1, besides performance and control effectiveness the research evaluated each context with regard to process sustainability by means of two measures of performance. The energy intensity was quantified as the total energy consumed per processed application. Optimised digital control processes (especially MPC and discrete-event) evidenced lower energy per unit output due to more efficient task scheduling, avoidance of idle resources, and minimisation of repetition and waste caused by bottlenecks.

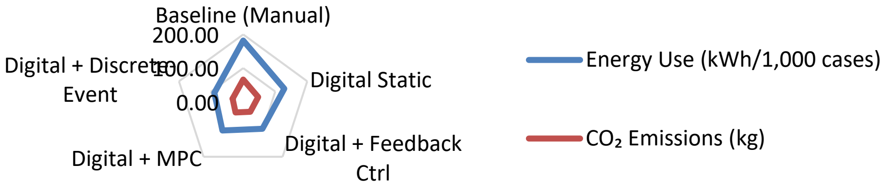

Figure 1: CO_2 Emission and energy use comparison across five simulated control scenarios

According to the findings, control-based process design not only improves efficiency but also directly contributes to sustainability goals. By reducing energy use, load balancing, and task reduction, these strategies support leaner paradigms in public administration, especially when complemented with structural modeling using P-graph. The results indicate that all of the control methods performed better than the baseline on delay, with the discrete-event control performing best overall in responsiveness and utilization balance. All control strategies demonstrate distinctive strengths. Feedback control was best with low data requirements and continuous monitoring but slower to adjust under nonlinear development. MPC was best with structured workflows with pre-established patterns of demand. Discrete-event control, due to its increased complexity of implementation, showed most flexibility, stability, and scalability, especially when combined with P-graph structural optimization. The outcomes suggest that the fusion of discrete-event control logic with structural modeling using P-graph is a fruitful hybrid strategy to sustainable administrative process management. In practice, administrative workflow engineering with the introduction of control theory enables proactive adaptation to demand variation, efficient allocation of resources in hybrid digital/manual environments, and scenario-based assistance in decision-making for process redesign, automation, and policy analysis.

5. Conclusions

This study proposed a control-theoretic framework supported by structural modeling of P-graph to enhance administrative process effectiveness and operational sustainability scenario-by-scenario. Using the university enrollment process as a case study, five control conditions were evaluated including manual workflows to digitally optimized with feedback, model predictive, and discrete-event control strategies. The findings show that the integration of control theory in designing administrative processes has a dramatic decrease in mean processing delays, improves resource utilization, and increases flexibility in processes. Among all the strategies experimented with, discrete-event control, particularly in combination with P-graph-based structure optimization, was the most balanced among responsiveness, efficiency, and flexibility. In addition, the inclusion of sustainability measures, such as energy intensity and CO_2 emissions demonstrated that control-maximized workflows matter to environmental targets. The digital discrete-event scenario exhibited the least energy usage and carbon footprint, suggesting the feasibility of such methodologies to achieving operational and ecological sustainability in public services. This research was based on collected data and simulated process behavior, with data based generalized assumptions on task durations, energy profiles, and system parameters. Regarding limitations real-world variability, such as the behavioral factors, existing policy constraints, and unpredictable demand fluctuations were not fully captured. Moreover, cost implications of the implementation of advanced control mechanisms were not addressed in depth. Future research should focus on the development of a more advanced hybrid control model with more integration of P-graph logic into actual administrative systems. Real-time system data integration could allow adaptive control mechanisms that evolve over time as operational requirements change. Further research into multi-objective optimization could better optimize performance, cost, and sustainability goals. Lastly, extending the framework to other administrative functions, like financial dealings, compliance administration, or student assistance systems could extend and validate the model's versatility in broader public sector transformations.

Nomenclature

A - number of applications to process
D_{av} - average process delay per application
D_j - total process delay per application
E_i - energy consumption of task i, kWh
E_{total} - total energy consumed by the process, kWh
F - flexibility score of process configuration
N - number of tasks in the scenario process
N_f - number of feasible reconfigurations
$N_{f,max}$ - the total number of feasible process variants for the most flexible (hybrid) scenario
n_i - number of instances of task i in the process
PI - Performance Index relative to baseline
P_i - power consumption of device or activity used in task iii, kW
PI_s>1 - indicates a performance improvement
$Q_i(t)$ - queue length for task i at time t
R_i - number of resources assigned to task i
T_i - average processing time for task i
t_i - time required for task i, h
Ui - utilization of resource i
γ - grid-specific emission factor, 0.366 kg CO_2/kWh

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