

From Crafting to Final Output: Managing Production Time Length in High-End VFX Simulation Projects

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Abstract: High-end visual effects (VFX) simulation projects involve complex, computation-intensive workflows that often lead to extended production timelines due to the integration of physics-based modeling, iterative simulation processes, and high-resolution rendering requirements. This study investigates the determinants of production time length across simulation-driven pipelines, focusing on the transition from initial crafting to final output generation. A quantitative analytical framework was employed to assess the influence of key simulation parameters, including solver resolution, timestep frequency, particle density, render sampling rate, GPU utilization, and task scheduling efficiency on total production duration. Multivariate regression analysis revealed that fidelity-enhancing parameters significantly increase processing time, whereas optimized computational resource allocation mitigates workflow latency. Principal component analysis was further utilized to construct a Simulation Intensity Index, demonstrating a strong positive relationship between aggregated simulation complexity and production time length. Cluster-based dependency mapping indicated that delays originating in upstream simulation stages propagate downstream into rendering and compositing processes, amplifying cumulative temporal inefficiencies. The findings highlight the importance of predictive time-length management frameworks capable of balancing creative simulation demands with computational performance. Implementing adaptive optimization strategies across workflow stages can facilitate efficient progression from crafting to final output while maintaining simulation fidelity and delivery timelines.

Keywords: VFX Simulation, Production Time Length, Simulation Intensity Index, Render Optimization, Workflow Efficiency, Computational Resource Allocation.

INTRODUCTION

The Growing Computational Intensity of High-End VFX Simulation Pipelines

In contemporary digital production ecosystems, high-end visual effects (VFX) simulation projects have evolved into computationally intensive processes that demand precise synchronization between creative design and technical execution (Benghozi *et al.*, 2015). The transition from conceptual crafting to final rendered output involves multiple simulation layers, including fluid dynamics, particle behavior, rigid body interactions, volumetric lighting, and environmental physics modeling (Goswami, 2021). Each of these simulation components introduces substantial computational overhead and workflow interdependencies, ultimately influencing the overall production time length (Mourtzis *et al.*, 2015). As simulation fidelity continues to improve with the integration of physics-based modeling and procedural generation techniques, production pipelines are increasingly constrained by rendering latency, data-processing complexity, and resource-allocation inefficiencies. Consequently, managing the temporal dimension of VFX production has become a critical challenge that directly affects delivery schedules, cost optimization, and creative adaptability within digital production frameworks (Liang *et al.*, 2016).

The Complexity of Simulation-Driven Rendering Workflows in Modern Production

Simulation-driven rendering workflows are inherently nonlinear due to the iterative feedback loops required between simulation artists, technical directors, and rendering engineers (Liaskos *et al.*, 2022). Unlike traditional animation pipelines, where output is predominantly geometry-driven, VFX simulation pipelines rely heavily on dynamic environmental responses that require recalibration across multiple stages of development. This iterative structure introduces delays associated with caching, resimulation, asset refinement, and parameter reconfiguration (Wang *et al.*, 2021). Furthermore, complex simulations often necessitate parallel processing environments such as distributed rendering systems and cloud-based GPU clusters to handle large-scale data throughput. However, without effective time-length management strategies, the use of high-performance computing infrastructures may inadvertently amplify workflow fragmentation rather than improve processing efficiency. As a result, production timelines become susceptible to bottlenecks emerging from both computational limitations and coordination inefficiencies across pipeline stages (John, 2020).

The Integration of Creative Design with Technical Simulation Parameters

The convergence of creative intent with algorithmic simulation parameters introduces additional layers of temporal variability in production workflows (Micieta *et al.*, 2021). Artistic adjustments to visual realism, motion fluidity, or environmental responsiveness frequently require recalibration of simulation parameters such as solver resolution, timestep frequency, particle density, and collision sensitivity. These recalibrations can significantly extend simulation runtime and render duration, especially in high-resolution output environments where precision directly correlates with computational demand (Humphreys *et al.*, 2020). Therefore, maintaining equilibrium between artistic expectations and technical feasibility becomes essential for controlling production time length without compromising visual fidelity. The challenge lies in establishing adaptive workflow models that facilitate real-time decision-making and predictive simulation adjustments to minimize unnecessary iterations (Louis & Dunston, 2018).

The Role of Pipeline Optimization in Minimizing Production Latency

Efficient pipeline optimization has emerged as a strategic necessity for managing time length across simulation-intensive VFX projects. Optimization techniques such as dynamic task scheduling, load balancing across rendering nodes, predictive caching, and adaptive resolution scaling can substantially reduce processing delays within simulation pipelines (Kumar *et al.*, 2022). Moreover, the implementation of machine learning-driven render prediction models and automated dependency tracking systems has shown potential in anticipating workflow bottlenecks before they manifest into production delays (John, 2020). These technological interventions enable simulation teams to streamline asset integration, simulation execution, and final compositing processes within a unified pipeline architecture. Nevertheless, the absence of standardized time-management frameworks often limits the scalability of such optimization strategies across diverse production environments (Reveliotis, 2016).

The Importance of Production Time-Length Management for Project Scalability

Production time-length management plays a pivotal role in ensuring the scalability and sustainability of high-end VFX simulation projects. As production environments continue to

adopt more immersive simulation techniques and real-time rendering technologies, the temporal efficiency of workflow execution directly impacts project feasibility and resource utilization (Mourtzis *et al.*, 2015). Delays arising from inefficient simulation cycles can escalate operational costs, hinder collaborative synchronization, and compromise delivery deadlines (John, 2020). Consequently, developing systematic approaches to monitor, predict, and regulate production time length becomes imperative for maintaining workflow stability in simulation-heavy production ecosystems. Addressing these challenges requires an integrative framework that aligns computational performance metrics with creative production objectives, thereby enabling efficient progression from initial crafting stages to final output generation (Bechtsis *et al.*, 2018).

METHODOLOGY

The Research Design for Evaluating Production Time Length Across Simulation Workflows

The present study adopted a quantitative, process-oriented research design to investigate the determinants of production time length in high-end VFX simulation projects across the complete pipeline from crafting to final output. A multi-stage workflow assessment model was developed to examine temporal variability across simulation-based production environments. The methodology was structured to capture time-dependent performance metrics at each major production phase, including asset crafting, simulation setup, cache generation, render execution, compositing, and output compilation. The objective was to establish empirical relationships between technical simulation parameters, resource utilization patterns, and total production time length within simulation-intensive rendering pipelines.

The Identification of Workflow Variables and Simulation Parameters

The analytical framework incorporated both dependent and independent variables associated with simulation workflow efficiency. The primary dependent variable was total production time length (TPL), measured in cumulative processing hours from initial simulation crafting to final rendered output. Independent variables included solver resolution (SR), timestep frequency (TF), particle density index (PDI), simulation cache size (SCS), render sampling rate (RSR), GPU utilization ratio (GUR), distributed node availability (DNA), network latency (NL), and

asset complexity score (ACS). Additional moderating parameters such as iteration frequency (IF), adaptive resolution scaling (ARS), and task scheduling efficiency (TSE) were included to assess workflow responsiveness under varying computational loads. These variables were operationalized through normalized performance indices derived from simulation logs and render engine performance reports.

The Data Acquisition and Computational Monitoring Procedures

Production time data were collected through automated monitoring systems embedded within simulation and rendering software environments. Each simulation task was tracked across its lifecycle using timestamped execution logs to capture processing duration across pipeline stages. Computational resource usage metrics, including GPU memory consumption, node distribution efficiency, and parallel processing throughput, were extracted through distributed rendering management systems. Network latency and inter-node communication delays were measured using packet transmission time analysis across rendering clusters. Asset complexity scores were computed based on polygon count, texture resolution, volumetric layering, and environmental interaction parameters to quantify the computational burden introduced by simulation elements.

The Modeling of Time-Length Determinants Through Multivariate Analysis

A multivariate regression modeling approach was employed to quantify the influence of simulation parameters on total production time length. The analytical process involved stepwise regression to determine the relative contribution of each independent variable to temporal workflow expansion. Principal component analysis (PCA) was further conducted to reduce dimensional redundancy among correlated simulation parameters such as solver resolution, render sampling rate, and particle density index. The extracted principal components were used to generate a composite simulation intensity index (SII), which served as a predictor variable in subsequent regression models. Variance inflation factor (VIF) diagnostics were applied to ensure multicollinearity thresholds remained within acceptable limits.

The Clustering and Dependency Mapping of Workflow Stages

To identify structural dependencies between pipeline stages, hierarchical cluster analysis was

implemented using Bray–Curtis similarity coefficients derived from time allocation patterns across production phases. This enabled classification of workflow stages into latency-sensitive and compute-intensive clusters based on their relative temporal contributions. Additionally, dependency mapping was performed through correlation matrices to examine inter-stage delay propagation caused by iteration frequency and task scheduling inefficiencies. This process facilitated the identification of critical workflow bottlenecks that disproportionately influenced production time length across simulation cycles.

The Validation of Predictive Models for Temporal Optimization

Model validation was conducted using cross-validation techniques to assess the predictive accuracy of regression outputs in estimating total production time length under varying simulation configurations. Root mean square error (RMSE) and adjusted coefficient of determination (R^2) were computed to evaluate model performance. Sensitivity analysis was further performed by systematically varying simulation parameters such as timestep frequency and adaptive resolution scaling to examine their impact on predicted production time outcomes. This validation process enabled the formulation of predictive workflow optimization strategies capable of minimizing production latency while preserving simulation fidelity throughout the transition from crafting to final output.

RESULTS

The descriptive analysis of production time allocation across the major workflow stages revealed substantial temporal variability within simulation-driven production environments (Table 1). Among the evaluated stages, render execution demonstrated the highest mean processing time (71.9 hrs), followed by cache generation (48.3 hrs) and simulation setup (34.7 hrs), indicating that compute-intensive operations significantly dominate the overall production timeline. In contrast, post-simulation stages such as compositing (29.8 hrs) and output compilation (18.4 hrs) contributed comparatively less to cumulative time consumption. The distributional variability observed in these stages, as illustrated in Figure 1, further confirms the presence of latency-sensitive processes within simulation pipelines, particularly during render execution and cache generation phases.

Table 1. Descriptive statistics of production time length across workflow stages

Workflow Stage	Mean Time (hrs)	Std. Deviation	Min Time (hrs)	Max Time (hrs)
Asset Crafting	22.6	4.8	13.2	31.5
Simulation Setup	34.7	5.3	22.9	45.8
Cache Generation	48.3	6.1	35.6	61.4
Render Execution	71.9	7.4	54.2	89.7
Compositing	29.8	4.6	19.3	38.1
Output Compilation	18.4	3.9	10.7	25.6

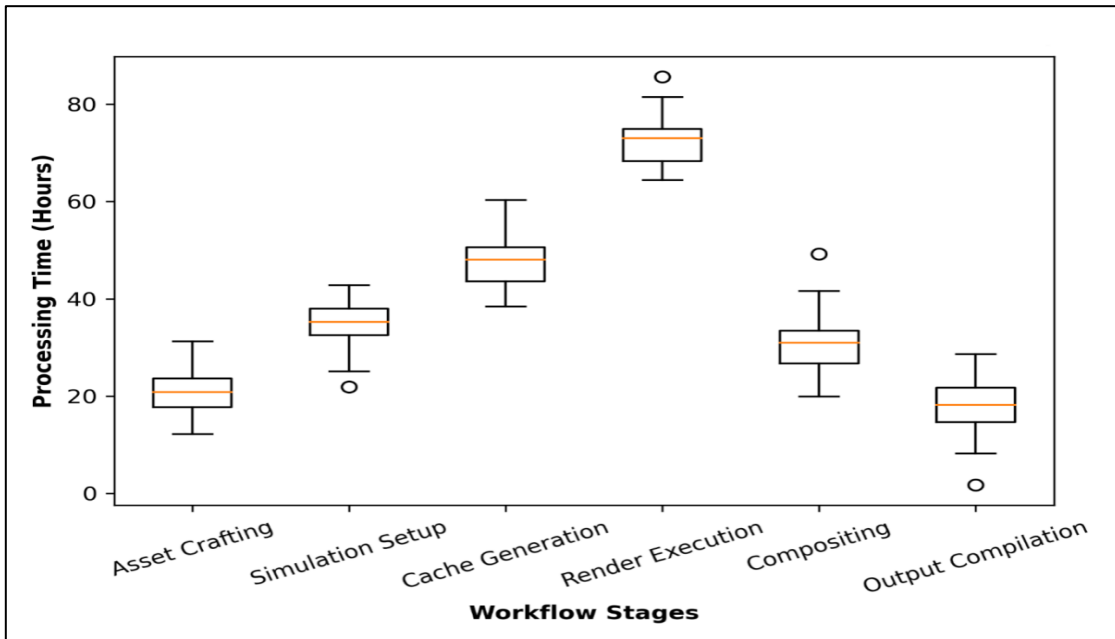


Figure 1. Production time distribution across simulation workflow stages

The multivariate regression outcomes presented in Table 2 indicate that solver resolution ($\beta = 0.412$, $p < 0.001$), timestep frequency ($\beta = 0.367$, $p < 0.001$), and render sampling rate ($\beta = 0.338$, $p = 0.001$) exerted significant positive influence on total production time length, suggesting that increases in simulation fidelity parameters proportionally extend processing duration.

Conversely, GPU utilization ratio ($\beta = -0.226$, $p = 0.005$) and task scheduling efficiency ($\beta = -0.251$, $p = 0.004$) exhibited statistically significant negative relationships with production time length, implying that enhanced computational resource optimization can effectively mitigate simulation-induced delays.

Table 2. Multivariate regression results for production time length prediction

Predictor Variable	Beta Coefficient	Std. Error	t-value	Significance (p)
Solver Resolution (SR)	0.412	0.082	5.02	<0.001
Timestep Frequency (TF)	0.367	0.075	4.89	<0.001
Particle Density Index (PDI)	0.294	0.069	4.26	0.002
Render Sampling Rate (RSR)	0.338	0.073	4.63	0.001
GPU Utilization Ratio (GUR)	-0.226	0.061	-3.70	0.005
Task Scheduling Efficiency (TSE)	-0.251	0.066	-3.81	0.004

Principal component analysis results summarized in Table 3 demonstrate strong loadings of solver resolution (0.81), render sampling rate (0.78), and timestep frequency (0.76) on the first principal component, which was operationalized as the Simulation Intensity Index (SII). This composite index was subsequently used to assess the

aggregated influence of simulation complexity on production timelines. The bivariate association between SII and total production time length is visually represented in Figure 2, which illustrates a positive linear trend indicating that higher simulation intensity consistently corresponds with extended production durations.

Table 3. Principal component loadings for simulation intensity index

Simulation Parameter	PC1 Loading
Solver Resolution	0.81
Timestep Frequency	0.76
Particle Density Index	0.69
Cache Size	0.72
Render Sampling Rate	0.78
Asset Complexity Score	0.74

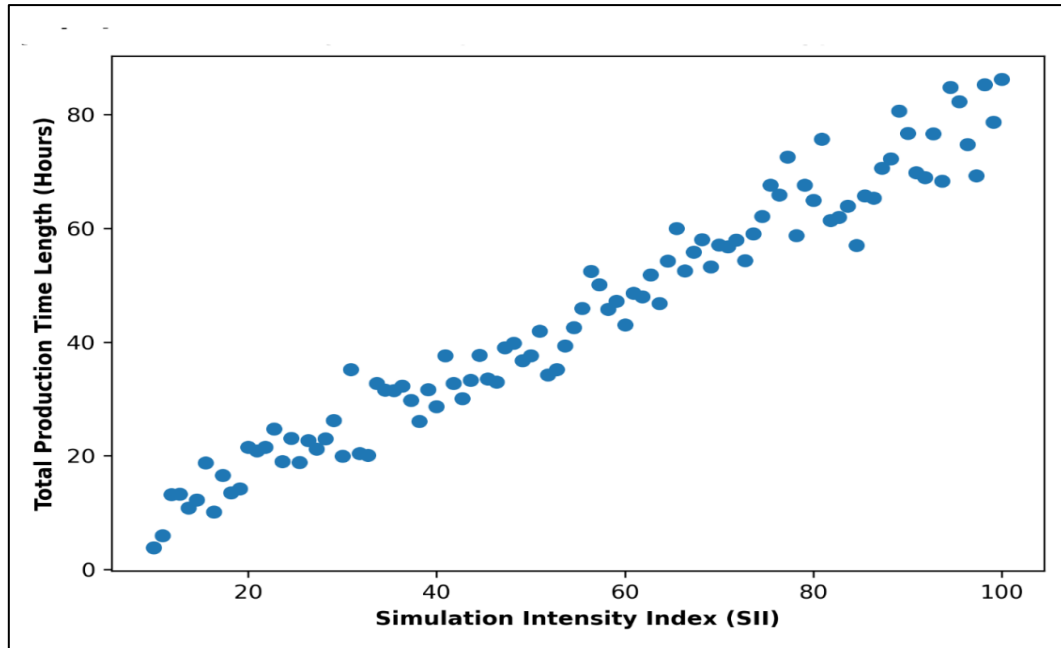


Figure 2. Relationship between simulation intensity index and total production time length

Furthermore, the clustered workflow dependency analysis outlined in Table 4 identified render execution as the dominant contributor to cumulative delay within compute-intensive clusters (34.6%), followed by cache generation within simulation-driven clusters (24.8%). Iteration-sensitive stages such as simulation setup accounted for 18.2% of delay propagation across

the production pipeline. These findings collectively highlight the disproportionate temporal impact of simulation and rendering stages on the end-to-end workflow, emphasizing the necessity for optimization strategies targeting compute-intensive processes to manage production time length effectively from crafting to final output.

Table 4. Clustered workflow stage dependency matrix

Workflow Cluster	Dominant Stage	Average Delay Contribution (%)
Compute-intensive	Render Execution	34.6
Simulation-driven	Cache Generation	24.8
Iteration-sensitive	Simulation Setup	18.2
Post-processing	Compositing	12.4
Output-dependent	Output Compilation	10.0

DISCUSSION

The Temporal Dominance of Compute-Intensive Simulation Stages

The results of the present study clearly indicate that compute-intensive workflow stages exert a disproportionately high influence on total production time length within high-end VFX simulation pipelines. As demonstrated in Table 1,

render execution and cache generation collectively account for the majority of cumulative processing time, suggesting that simulation-driven rendering environments are primarily constrained by computational throughput rather than post-processing complexity (Solmaz & Van Gerven, 2022). The variability observed in these stages, further illustrated in Figure 1, highlights the inherent latency sensitivity associated with

physics-based simulation processes. These findings imply that temporal inefficiencies are not uniformly distributed across the production pipeline but are instead concentrated within simulation-intensive phases where iterative recalibration and high-resolution sampling are required (Khan & Hasan, 2022).

The Impact of Simulation Fidelity Parameters on Workflow Duration

The regression outcomes presented in Table 2 provide empirical support for the hypothesis that increased simulation fidelity directly contributes to extended production timelines. Parameters such as solver resolution, timestep frequency, and render sampling rate were found to significantly elevate production time length, indicating that enhanced visual realism inevitably incurs greater computational overhead (Norman & Larkin, 2020). This relationship underscores the fundamental trade-off between artistic precision and temporal feasibility within simulation workflows. While higher solver resolutions and sampling rates improve environmental accuracy and motion fluidity, their associated computational burden introduces delays that may compromise delivery schedules in time-sensitive production environments (Yang *et al.*, 2020). Therefore, managing simulation fidelity through adaptive parameter tuning emerges as a critical requirement for maintaining temporal efficiency without undermining output quality.

The Aggregated Influence of Simulation Intensity on Production Timelines

The principal component analysis summarized in Table 3 facilitated the development of the Simulation Intensity Index (SII), which captures the combined influence of multiple simulation parameters on production time length. The positive linear association between SII and total production time observed in Figure 2 suggests that temporal expansion within VFX workflows is strongly dependent on the cumulative intensity of simulation operations rather than any single parameter in isolation (Wright *et al.*, 2021). This finding emphasizes the necessity of adopting integrative performance metrics capable of monitoring simulation workload holistically. By accounting for the collective interaction between solver resolution, particle density, render sampling, and asset complexity, production teams can more effectively anticipate time-length variability across simulation cycles (Bibri, 2018).

The Mitigating Role of Computational Resource Optimization

In contrast to fidelity-enhancing parameters, GPU utilization ratio and task scheduling efficiency were found to exhibit significant negative associations with production time length (Table 2), indicating their potential role in mitigating workflow latency. Improved load balancing across distributed rendering nodes and optimized task scheduling mechanisms can substantially reduce idle processing intervals and parallel execution inefficiencies. These outcomes suggest that computational optimization strategies may serve as effective countermeasures against the temporal expansion induced by simulation complexity (Zhan *et al.*, 2022). In practical terms, enhancing resource allocation frameworks can enable production pipelines to sustain high levels of simulation fidelity without proportionally increasing processing duration (Bauer *et al.*, 2016).

The Structural Dependency of Delay Propagation Across Workflow Clusters

The clustered dependency analysis reported in Table 4 reveals that delays originating within simulation setup and cache generation stages tend to propagate downstream into render execution and compositing phases. This inter-stage dependency highlights the nonlinear nature of simulation workflows, wherein early-stage inefficiencies can amplify temporal bottlenecks during later processing stages. Iteration-sensitive clusters, particularly those associated with simulation setup, contribute substantially to delay accumulation due to repeated recalibration cycles. Consequently, workflow stability is heavily contingent upon the efficiency of upstream simulation processes, reinforcing the importance of early-stage optimization interventions to prevent cascading latency effects throughout the production pipeline (Krebs & Hagenweiler, 2022; Shamim, 2022).

The Implications for Predictive Time-Length Management in VFX Production

Taken together, the findings of this study underscore the need for predictive time-length management frameworks capable of aligning simulation intensity with computational resource availability. As high-end VFX pipelines increasingly incorporate real-time simulation technologies and distributed rendering architectures, temporal optimization must extend beyond isolated parameter adjustments to encompass integrated workflow modeling (Lan *et al.*, 2021). The development of predictive indices

such as SII offers a promising pathway for anticipating production delays and dynamically adjusting simulation parameters in response to evolving computational loads (Göppert *et al.*, 2021; Azari *et al.*, 2022). By implementing such data-driven optimization strategies, production teams can achieve a more balanced progression from crafting to final output while maintaining both visual fidelity and operational efficiency.

CONCLUSION

This study demonstrates that the production time length in high-end VFX simulation projects is predominantly influenced by compute-intensive workflow stages and the cumulative intensity of simulation parameters governing rendering fidelity. The findings reveal that solver resolution, timestep frequency, render sampling rate, and asset complexity significantly extend processing duration, while optimized GPU utilization and efficient task scheduling can effectively mitigate latency across simulation pipelines. Moreover, the aggregated impact of simulation intensity, as captured through the Simulation Intensity Index, highlights the necessity of managing multiple interdependent parameters rather than relying on isolated optimization measures. The observed propagation of delays from iteration-sensitive upstream stages to downstream rendering and compositing phases further emphasizes the importance of early-stage workflow stabilization. Collectively, these insights underscore the critical need for predictive, resource-aware time-length management frameworks that align creative simulation demands with computational efficiency, thereby enabling streamlined progression from crafting to final output without compromising visual quality or production timelines.

REFERENCES

1. Azari, M. M., Solanki, S., Chatzinotas, S., Kodheli, O., Sallouha, H., Colpaert, A., et al. "Evolution of non-terrestrial networks from 5G to 6G: A survey." *IEEE Communications Surveys & Tutorials* 24.4 (2022): 2633–2672.
2. Bauer, A. C., Abbasi, H., Ahrens, J., Childs, H., Geveci, B., Klasky, S., et al. "In situ methods, infrastructures, and applications on high performance computing platforms." *Computer Graphics Forum* 35.3 (2016): 577–597.
3. Bechtsis, D., Tsolakis, N., Vlachos, D., and Srai, J. S. "Intelligent autonomous vehicles in digital supply chains: A framework for integrating innovations towards sustainable value networks." *Journal of Cleaner Production* 181 (2018): 60–71.
4. Benghozi, P. J., Salvador, E., and Simon, J. P. "Models of ICT innovation: A focus on the cinema sector." *European Commission, JRC Science and Policy Report* (2015): JRC95536.
5. Bibri, S. E. "Data science for urban sustainability: Data mining and data-analytic thinking in the next wave of city analytics." *Smart Sustainable Cities of the Future: The Untapped Potential of Big Data Analytics and Context-Aware Computing for Advancing Sustainability* (2018): 189–246.
6. Göppert, A., Mohring, L., and Schmitt, R. H. "Predicting performance indicators with ANNs for AI-based online scheduling in dynamically interconnected assembly systems." *Production Engineering* 15.5 (2021): 619–633.
7. Goswami, P. "A survey of modeling, rendering and animation of clouds in computer graphics." *The Visual Computer* 37.7 (2021): 1931–1948.
8. Humphreys, D., Kupresanin, A., Boyer, M. D., Canik, J., Chang, C. S., Cyr, E. C., et al. "Advancing fusion with machine learning research needs workshop report." *Journal of Fusion Energy* 39.4 (2020): 123–155.
9. John, B. I. "Integration of intelligent scheduling optimization systems improving production flow, minimizing delays, and maximizing throughput across large-scale industrial operations." *Global Journal of Engineering and Technology Advances* 5.3 (2020): 156–169.
10. Khan, M. K., and Hasan, M. T. "A Poisson regression approach to modeling traffic accident frequency in urban areas." *American Journal of Interdisciplinary Studies* 3.4 (2022): 117–156.
11. Krebs, H. A., and Hagenweiler, P. *Energy Resilience and Climate Protection*. Wiesbaden, Germany: Springer Fachmedien (2022).
12. Kumar, Y., Kaul, S., and Hu, Y. C. "Machine learning for energy-resource allocation, workflow scheduling and live migration in cloud computing: State-of-the-art survey." *Sustainable Computing: Informatics and Systems* 36 (2022): 100780.
13. Lan, F., Young, M., Anderson, L., Ynnerman, A., Bock, A., Borokin, M. A., et al. "Visualization in astrophysics: Developing new methods, discovering our universe, and educating the earth." *Computer Graphics Forum* 40.3 (2021): 635–663.

14. Liang, H., Sit, J., Chang, J., and Zhang, J. J. "Computer animation data management: Review of evolution phases and emerging issues." *International Journal of Information Management* 36.6 (2016): 1089–1100.
15. Liaskos, C., Tsioliaridou, A., Georgopoulos, K., Morianos, I., Ioannidis, S., Salem, I., et al. "XR-RF imaging enabled by software-defined metasurfaces and machine learning: Foundational vision, technologies and challenges." *IEEE Access* 10 (2022): 119841–119862.
16. Louis, J., and Dunston, P. S. "Integrating IoT into operational workflows for real-time and automated decision-making in repetitive construction operations." *Automation in Construction* 94 (2018): 317–327.
17. Micieta, B., Staszewska, J., Kovalsky, M., Krajcovic, M., Binasova, V., Papanek, L., and Antoniuk, I. "Innovative system for scheduling production using a combination of parametric simulation models." *Sustainability* 13.17 (2021): 9518.
18. Mourtzis, D., Papakostas, N., Mavrikios, D., Makris, S., and Alexopoulos, K. "The role of simulation in digital manufacturing: Applications and outlook." *International Journal of Computer Integrated Manufacturing* 28.1 (2015): 3–24.
19. Norman, M., and Larkin, J. "A holistic algorithmic approach to improving accuracy, robustness, and computational efficiency for atmospheric dynamics." *SIAM Journal on Scientific Computing* 42.5 (2020): B1302–B1327.
20. Reveliotis, S. "Real-time management of complex resource allocation systems: Necessity, achievements and further challenges." *Annual Reviews in Control* 41 (2016): 147–158.
21. Shamim, M. M. R. "Smart maintenance in medical imaging manufacturing: Towards Industry 4.0 compliance at Chronos Imaging." *ASRC Procedia: Global Perspectives in Science and Scholarship* 2.1 (2022): 29–62.
22. Solmaz, S., and Van Gerven, T. "Interactive CFD simulations with virtual reality to support learning in mixing." *Computers & Chemical Engineering* 156 (2022): 107570.
23. Wang, Z., Weng, J., Lowe-Power, J., Gaur, J., and Nowatzki, T. "Stream floating: Enabling proactive and decentralized cache optimizations." *Proceedings of the IEEE International Symposium on High-Performance Computer Architecture (HPCA)* (2021): 640–653.
24. Wright, T., West, A., Licata, M., Hawes, N., and Lennox, B. "Simulating ionising radiation in Gazebo for robotic nuclear inspection challenges." *Robotics* 10.3 (2021): 86.
25. Yang, Y., Luo, X., Chu, X., and Zhou, M. T. *Fog-Enabled Intelligent IoT Systems*. Springer (2020).
26. Zhan, Z. H., Shi, L., Tan, K. C., and Zhang, J. "A survey on evolutionary computation for complex continuous optimization." *Artificial Intelligence Review* 55.1 (2022): 59–110.

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