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Forecasting Global Digital Infrastructure Capacity with an Optimized Discrete Grey Model

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Abstract: The rapid expansion of digital infrastructure presents significant forecasting and strategic planning challenges for investors and corporate decision-makers. This study applies the DGM (1,1,α) grey forecasting model to project the growth of four critical variables to 2030: global network traffic, data creation, data centre supply, and data centre demand, using secondary data. The model demonstrates high in-sample accuracy, with Mean Absolute Percentage Errors (MAPE) below 1.35%. A comparative analysis with industry benchmarks reveals strong alignment, validating the model's robustness. Key findings project sustained near-exponential growth and a critical narrowing of the global supply-demand margin. The results highlight impending market tightness and provide a quantitative framework for strategic capacity planning, capital allocation, and risk mitigation in the digital infrastructure sector, directly supporting data-driven management science applications.

Keywords: Grey Model; Forecast; Digital Infrastructure; Data Centre; Strategic Management; Capacity Planning

1. Introduction

The global digital infrastructure landscape is undergoing unprecedented transformation, driven by the convergence of artificial intelligence, ubiquitous cloud computing, and evolving data governance frameworks (Nookala, 2024). As society becomes increasingly data-centric, the physical and logical foundations that support digital activities—particularly data centers and the networks that interconnect them—have emerged as critical determinants of economic competitiveness, innovation capacity, and national security (Shukla *et al.*, 2023). Understanding the future trajectory of these infrastructures is not merely an academic exercise but a strategic imperative for policymakers, investors, and technology leaders.

However, forecasting in this domain presents significant challenges. Digital infrastructure evolution is influenced by a complex interplay of technological breakthroughs, regulatory shifts, market dynamics, and societal adoption patterns (Tilson *et al.*, 2010). Traditional forecasting methods, which often rely on large historical datasets and linear assumptions, may struggle to capture the disruptive, non-linear growth characteristics typified by phenomena such as the generative AI explosion or the rapid decentralization of computing through edge architectures (Bunn, 1996; Armstrong, 2001). In such environments, the Grey System Theory – and specifically the DGM (1,1,α) model – offers a valuable methodological alternative (Javed & Cudjoe, 2022). Designed to generate reliable forecasts with limited data and under conditions of uncertainty, grey modeling is particularly well-suited to analyzing emerging, high-growth sectors where historical series are short and future trends are inherently ambiguous.

This study applies the DGM (1,1,α) forecasting model to four pivotal indicators extracted from the Global Data Centre Insights 2024 report (Sanger & Sriram, 2024), each representing a core dimension of digital infrastructure scale and velocity: (a) Global annual network traffic data, (b) Annual global data creation (in zettabytes), (c) Global data center supply (in gigawatts), and (d) Global data center demand (in gigawatts). These variables collectively capture the digital ecosystem's intensity: data generation fuels network traffic, which in turn drives demand for processing and storage capacity, necessitating commensurate investments in physical infrastructure. By projecting these metrics through 2030, this research aims to quantify anticipated growth pathways, assess potential imbalances between supply and demand, and illuminate the systemic pressures that may shape the next phase of digital expansion.

The analysis not only provides actionable forecasts for stakeholders but also demonstrates the applicability of grey system models in infrastructure economics. In doing so, it contributes to a more nuanced understanding of how digital capabilities scale, where bottlenecks may arise, and how strategic planning can adapt to a future defined by exponential data growth and computational demand. In the succeeding section first, we will review the relevant literature, and then data collection and analyses methods will be introduced. Later, results and important findings will be discussed. In the end, the study will be concluded with some important recommendations.

2. Literature review

2.1 Role of Digital Infrastructure in the Modern Economy

Digital infrastructure, encompassing data centers, fiber optic networks, and cloud platforms, has evolved from a supportive utility to a core driver of global economic activity and innovation. Scholarly consensus positions it as a critical form of 21st-century capital, essential for productivity, competitiveness, and societal function (Hussain, 2024). The rise of data-intensive paradigms – including big data analytics, the Internet of Things (IoT), and artificial intelligence – has exponentially increased dependence on reliable, scalable, and low-latency computational resources (Al-Atroshi & Zeebaree, 2024). This dependency frames data centers not merely as real estate assets but as the brains of the digital economy, where the physical and virtual worlds converge (Maak, 2022).

Concurrently, regulatory landscapes are shaping infrastructure geography. The proliferation of data sovereignty laws (e.g., General Data Protection Regulation in Europe, various national data localization policies) necessitates in-country or in-region data storage, fragmenting global cloud architectures and spurring localized infrastructure investment (TOI, 2025; Olorunlana, 2025). This tension between globally scaled technology platforms and nationally bounded regulatory regimes forms a key dynamic in infrastructure planning and investment thesis development, as noted by Sanger and Sriram (2024), which highlights it as a secular growth driver.

2.2 Forecasting Challenges in a High-Velocity Sector

Accurately forecasting the growth of digital infrastructure is a complex issue. Traditional econometric models, which often rely on long-term historical data and assumptions of linearity or stable cyclicality, are frequently ill-suited to a sector characterized by disruptive technological shocks and exponential growth patterns (Graf, 2002; Moshiri & Cameron, 2000). For instance, the advent of generative AI has abruptly recalibrated projections for compute density and power consumption, a phenomenon poorly captured by trend extrapolation (Tsai *et al.*, 2023).

Academic and industry forecasts typically employ a mix of methods: (a) Top-down models extrapolate from macroeconomic indicators, e.g., internet penetration rates, and mobile subscription data (Nyman *et al.*, 2014; Boamah, 2021); (b) Bottom-up models aggregate demand forecasts from hyperscalers, e.g., enterprise IT budgets, and specific application workloads (Duarte & Rua, 2007); (c) Technology adoption curves (e.g., Bass diffusion models) are used to model the uptake of cloud services or IoT devices (Daim & Suntharasaj, 2009).

However, these approaches often struggle with the rapid convergence of technologies, especially in uncertain environments. The inherent uncertainty and limited length of reliable, high-frequency time-series data for nascent trends (like AI workload power demand) create a significant forecasting gap (Makridakis *et al.*, 2018; Mossavar-Rahmani & Zohuri, 2025). This gap necessitates alternative modeling philosophies that can produce robust insights from sparse data.

2.3 Grey Forecasting

Grey System Theory, pioneered by Ju-long (1982), was developed explicitly to study systems with partial information, where some system parameters are known and others are unknown. It is distinguished from "black box" models (where internal mechanics are entirely unknown) and "white box" models (where all information is clear). The core strength of grey models lies in their ability to generate credible forecasts with as few as four data points, making them invaluable for analyzing emerging trends (Wang & Wang, 2025).

The foundational grey forecasting model is GM(1,1), a first-order, single-variable differential equation model. Its derivative, DGM (1,1) (Discrete Grey Model), and its optimized versions like DGM (1,1,α), which introduces a dynamic background coefficient, offer improved fitting accuracy and stability, especially for sequences with nonlinear growth characteristics (Javed *et al.*, 2025). These models have been successfully applied across diverse fields facing data scarcity. For instance, Ouali *et al.* (2024) used a grey forecasting model to forecast the growth in mobile cellular subscriptions and secure internet servers in the U.S.A. and China. Cudjoe *et al.* (2023) used a grey forecasting model to forecast annual plastic waste in China. Pandey *et al.* (2023) used a grey forecasting model to predict non-renewable and renewable energy production in India. Podrecca and Sartor (2023) used grey forecasting models to forecast the diffusion of ISO/IEC 27001 certifications in the world. The grey forecasting models usually involves data sequence processing, model construction, parameter estimation, and forecast accuracy measurement (often using metrics like Mean Absolute Percentage Error) (Rajesh, 2025). Its procedural rigor and flexibility have cemented its role in the forecaster's toolkit for uncertain environments.

While the grey system models are well-established in forecasting energy demand (Tian *et al.*, 2021) and industrial outputs (Wang & Hsu, 2008), their application to the forecasting of digital infrastructure capacity remains under-explored in academic literature (Ouali *et al.*, 2024). A systematic, model-driven examination of the interlinked growth trajectories of data creation, network traffic, data center supply, and data center demand – using a robust small-data method like DGM(1,1,α) – is not evident in the current body of research. Studies that have been conducted often rely on proprietary models or inaccessible data sources (see, e.g., Sanger & Sriram, 2024). The current study will fill this gap by bringing methodological rigor and transparency to the strategic forecasting of digital infrastructure

3. Research methodology

3.1 Data Collection

This study employs a data-driven quantitative forecasting approach centered on the DGM(1,1,α) model. The research process followed four structured phases: The first phase involved data collection and variable selection. Historical data for the four key variables (2019-2023/2024) was extracted from the Global Data Centre Insights 2024 report (Sanger & Sriram, 2024). These variables were selected for their foundational role in quantifying digital ecosystem scale and interlinked growth. The second phase was about the application of the model on this data. The DGM (1,1,α) model was chosen for its proven efficacy in forecasting with small, non-linear datasets. Each time series was independently modeled. The α parameter was computationally optimized for each variable to minimize fitting error, capturing unique growth dynamics. The third phase involved, forecast generation and validation. The fitted models were used to generate forecasts for 2024/2025-2030. In-sample model accuracy was rigorously validated by calculating the Mean Absolute Percentage Error (MAPE) between the model's fitted values and the actual historical data. The last phased involves comparative analysis and interpretation. To ground the analysis in a business context, the 2024-2027 forecasts were compared to independent projections from the GDCI 2024 report. The MAPE was calculated for this comparison period to quantify alignment and divergence, forming the basis for a discussion on strategic implications and market dynamics.

3.2 Optimized Discrete Grey Model of Forecasting

DGM (1,1,α) is the generalized form of DGM (1,1), which was developed by Xie and Liu (2009). DGM (1,1,α) was proposed by Javed and Cudjoe (2022). First of all, the Posterior Variance Test (Javed, 2023) was used for ex-ante evaluation of the forecasting models. Once, the test was passed by the model, it was applied using the following steps. Let the sequence of actual data is

$$X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \dots\ x^{(0)}(n)\right), x^{(0)}(k) \geq 0$$

and the sequence of conformable fractional accumulated data of $X^{(0)}$ is

$$X^{(\alpha)} = \left(x^{(\alpha)}(1), x^{(\alpha)}(2), \dots\ x^{(\alpha)}(n)\right)$$

where, $x^{(\alpha)}(k) = \sum_{i=1}^{k}\left(\frac{x^{(0)}(i)}{i^{1-\alpha}}\right), k = 1,2,\dots,n,$ for $\alpha \in (0,1]$. The discrete form of GM(1,1) with parameters β_1 and β_2, will be defined as

$$x^{(\alpha)}(k+1) = \beta_1 x^{(\alpha)}(k) + \beta_2$$

where β_1 and β_2 can be estimated through the Least Square method i.e.,

$$\hat{\beta} = [\,\beta_1, \beta_2]^T = [B^T B]^{-1} B^T Y$$

where,

$$B = \begin{bmatrix} x^{(\alpha)}(1) & 1 \\ x^{(\alpha)}(2) & 1 \\ \vdots & \vdots \\ x^{(\alpha)}(n-1) & 1 \end{bmatrix} \quad \text{and} \quad Y = \begin{bmatrix} x^{(\alpha)}(2) \\ x^{(\alpha)}(3) \\ \vdots \\ x^{(\alpha)}(n) \end{bmatrix}$$

The time response function of the grey model is expressed as

$$\hat{x}^{(\alpha)}(k) = {\beta_1}^{k}\left(x^{(0)}(1) - \frac{\beta_2}{1-\beta_1}\right) + \frac{\beta_2}{1-\beta_1} \quad, k = 2, 3\ \dots, n$$

The inverse conformable fractional accumulation is given by,

$$\hat{x}^{(0)}(k) = k^{1-\alpha}\left(\hat{x}^{(\alpha)}(k) - \hat{x}^{(\alpha)}(k-1)\right),\ k = 1,2,\dots,n;\ \hat{x}^{(0)}(0) = 0$$

The time-response function of $X^{(0)}$ is given by

$$\hat{x}^{(0)}(k) = k^{1-\alpha}(\beta_1 - 1)\left(x^{(0)}(1) - \frac{\beta_2}{1-\beta_1}\right){\beta_1}^{k-1}, k = 2,3,\dots,n$$

whereas, $\hat{x}^{(0)}(1) = x^{(\alpha)}(1) = x^{(0)}(1)$. For the complete detail on the model, its parameters, and properties, Javed and Cudjoe (2022) should be referred to.

3.2 Mean Absolute Percentage Error

The Mean Absolute Percentage Error (MAPE) is a widely used statistical measure of forecast accuracy. It calculates the average absolute percentage difference between forecasted values and actual observed values. A lower MAPE indicates a more accurate forecasting model. In this study, MAPE serves two critical purposes: first, to validate the in-sample fit of the DGM (1,1,α) model against historical data, where low values confirm model reliability; and second, to quantitatively compare our model's out-of-sample forecasts with an independent industry benchmark (GDCI 2024), providing a standardized metric to assess consensus or divergence in future outlooks. Its interpretation as a percentage makes it intuitively valuable for managerial decision-making, clearly communicating the magnitude of forecast error. The MAPE (%) is given by (Javed & Cudjoe, 2020),

$$MAPE(\%) = \frac{1}{n} \times \sum_{k=1}^{n} \left| \frac{x(k) - \hat{x}(k)}{x(k)} \right| \times 100$$

where $x(k)$ and $\hat{x}(k)$ are indicative of both observe and simulate (forecast) values obtained through the model. According to the scale proposed by Javed and Cudjoe (2020), a MAPE (%) of less than 20% reflects a good prediction:

$$MAPE(\%) = \begin{cases} < 10 & Highly\ accurate\ forecast \\ 10{\sim}20 & Good\ forecast \\ 20{\sim}30 & Reasonable\ forecast \\ > 30 & Inaccurate\ forecast \end{cases}$$

4. Results

4.1 Model Performance and Forecast Accuracy

The application of the DGM (1,1,α) model to the four key digital infrastructure variables yielded forecasts with high statistical accuracy. The in-sample MAPE for the period 2019-2023/2024 was exceptionally low for all variables: 0.067% for global network traffic, 1.341% for global data created, 0.118% for data centre supply, and 0.122% for data centre demand (see *Tables 1* and *2*). These results confirm the model's robust fit to the historical data, validating its use for forward projection. The model's inherent strength in handling small, non-linear datasets is clearly demonstrated, with the optimized α parameter successfully capturing the unique growth dynamics of each series.

A critical comparison was made between the forecasts generated by our DGM (1,1,α) model (hereafter "model estimates") and the independent projections for 2024-2027 published in the Global Data Centre Insights 2024 report ("GDCI estimates"). The MAPE for this out-of-sample comparison period reveals a close but nuanced alignment between the two forecasting sources. The forecasts for Global Data Created showed the strongest agreement (MAPE = 1.51%), indicating a high degree of consensus on the trajectory of data generation. Forecasts for Global Data Centre Demand also aligned well (MAPE = 3.45%). Slightly larger, yet still reasonable, divergences were observed for Global Network Traffic (MAPE = 4.55%) and Global Data Centre Supply (MAPE = 5.09%). These variances likely stem from differences in methodological approach; while our model extrapolates purely from the historical time series, the GDCI estimates likely incorporate proprietary market intelligence, granular capacity pipelines, and qualitative assessments of investment plans.

4.2 Analysis of Projections and Growth Dynamics

The forecast results from both our model and the GDCI report paint a picture of sustained, robust growth across all four metrics through 2027 and beyond. The estimated α parameters

Table 1. The forecasting of Network Traffic Data and Global Data Created

	Global network traffic data[a]			**Global Data Created (ZB)[b]**		
	Actual data	DGM (1,1,α)	GDCI[c]	Actual data	DGM (1,1,α)	GDCI[c]
2019	100	100		41	41	
2020	150	150		64	64	
2021	199	199		79	80	
2022	253	253		97	99	
2023	316	316		125	121	
2024		388	393	147	149	
2025		473	492		182	181
2026		572	610		223	222
2027		689	741		273	282
2028		826			333	
2029		986			407	
2030		1174			496	
α		0.664			0.935	
MAPE (%) in-sample		0.067%			1.341%	
MAPE (%) – benchmark[d]			4.55%			1.51%

[a] *Indexed as of 2019, i.e., the value for 2019 is set to 100 and subsequent years show growth relative to 2019.*
[b] *Zettabytes*
[c] *The GDCI estimates are from Sanger and Sriram (2024).*
[d] *MAPE* (%) with respect to *industry benchmarks i.e., the GDCI estimates.*

Table 2. The forecasting of global data centre supply and demand

	Global Data Centre Supply (GW)[e]			**Global Data Centre Demand (GW)[e]**		
	Actual data	DGM (1,1,α)	GDCI	Actual data	DGM (1,1,α)	GDCI
2019	21.2	21.2		18.4	18.4	
2020	24.0	24.0		20.9	20.9	
2021	27.0	27.1		23.8	23.8	
2022	30.6	30.6		27.0	27.0	
2023	34.5	34.5		30.5	30.6	
2024	38.9	38.9		34.7	34.6	
2025		43.9	45.1		39.2	39.8
2026		49.6	52.2		44.4	46.0
2027		56.0	60.6		50.2	53.1
2028		63.2			56.8	
2029		71.3			64.2	
2030		80.5			72.6	
α		1.00			0.981	
MAPE (%) in-sample		0.118%			0.122%	
MAPE (%) - benchmark			5.09%			3.45%

[e] *Gigawatts*

provide insight into the nature of this growth: (a) Network Traffic (α=0.664) and Data Created (α=0.935) exhibit α values significantly below 1, indicative of a growth pattern that is strong but gradually decelerating from a previously super-exponential phase. This suggests a maturation of the underlying drivers, though from a very high baseline. (2) Data Centre Supply (α=1.00) and Demand (α=0.981) have α values very close to 1, signaling near-exponential, constant-rate growth. This reflects the capital-intensive, project-led nature of infrastructure deployment, which is struggling to accelerate further due to the significant barriers to entry outlined in the GDCI report (e.g., supply chain, power, permitting). The analyses are shown in *Figures 1* and *2*.

A pivotal finding for strategic planning is the erosion of the relative supply buffer. While the absolute difference between supply and demand (in GW) increases, the growth rate of demand is so rapid that the surplus as a percentage of total market demand is projected to shrink. This buffer decreases from $\sim 15\% \left(=\frac{21.2-18.4}{18.4}\right)$ in 2019 to $\sim 11\% \left(=\frac{80-73}{73}\right)$ by 2030 in our model, with the GDCI 2027 estimate showing a similar compression to $\sim 14\% \left(=\frac{60.6-53.1}{53.1}\right)$. From a management perspective, this shrinking percentage buffer is what signals tightening market conditions. A 7 GW surplus in a 73 GW market (2030) represents a much leaner cushion against demand shocks or supply delays than a 2.8 GW surplus in an 18.4 GW market (2019). While the absolute surplus in

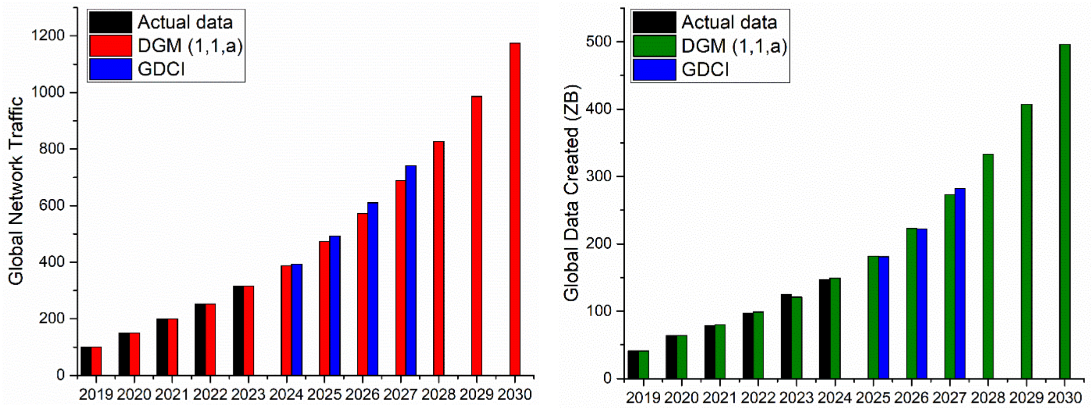

Fig 1. The projections of Network Traffic Data and Global Data Created

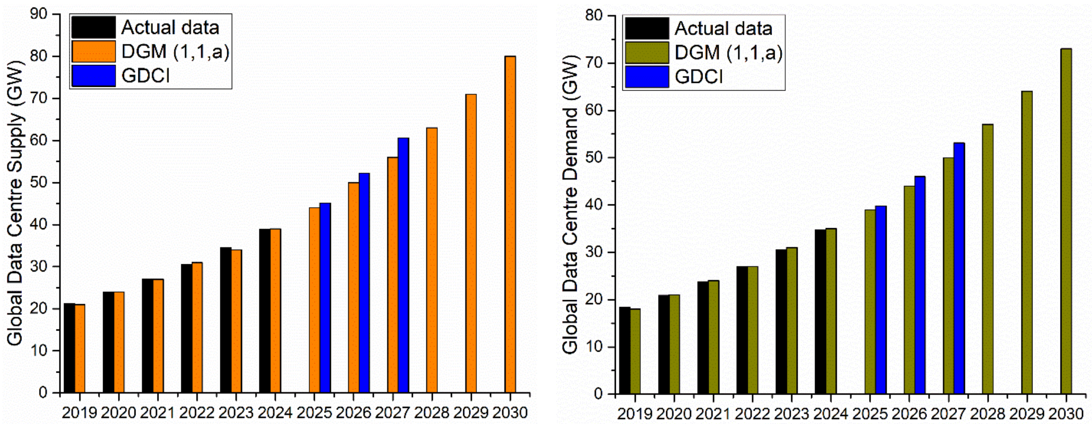

Fig 2. The forecasting of global data centre supply and demand projections

GW grows, the buffer ratio (or reserve margin) shrinks because demand grows even faster. It indicates reduced slack in the system, leading to decreased tenant bargaining power, reduced flexibility for operators, and the potential for localized shortages even while a global aggregate surplus exists. This perfectly aligns with observable market phenomena like rising lease rates and longer lead times (McKinsey, 2024).

Furthermore, the growth rate of Data Created is forecasted to outpace that of Data Centre Supply & Demand in the long-term model projection. This implies an increasing "density" of storage and computation, where more data must be processed, stored, or discarded per unit of available infrastructure power. This trend directly supports the industry shift towards higher rack densities, advanced cooling solutions, and efficiency gains driven by AI and specialized hardware.

4.3 Implications

The analysis confirms that the global digital infrastructure ecosystem is on a steep, non-linear growth trajectory. The strong performance of the DGM(1,1,α) model validates Grey System Theory as a potent tool for forecasting in this data-limited, high-uncertainty domain. The minor discrepancies between the model estimates and the GDCI estimates highlight different forecasting philosophies while converging on the central trend of robust growth.

The most significant finding for strategic management is the projected compression of the supply buffer. While the absolute difference between supply and demand (in GW) increases, the buffer ratio—the surplus expressed as a percentage of total demand—is forecasted to shrink from approximately 15% in 2019 to about 10% by 2030. This indicates that the system's effective slack is diminishing relative to its scale. This erosion of the relative buffer has direct and meaningful business implications: (a) A tighter buffer means less immediately available capacity in the market.

Tenants, especially those with urgent or large-scale requirements, lose leverage, which manifests in rising lease rates and stricter contract terms. (b) The shrinking cushion amplifies the risk of missing capacity needs due to lead times (2-4 years for new builds). Companies must shift from just-in-time procurement to strategic, long-term capacity planning and reservation. (c) A 10% buffer provides significantly less protection against a sudden demand surge (e.g., from a new AI model rollout) than a 15% buffer does in a smaller market. This increases systemic risk and volatility. (d) This quantitative projection of buffer compression directly explains the observable industry phenomena cited in reports: prolonged lead times, rising costs, and concerns over future shortages, even while aggregated global numbers show a surplus. Therefore, for stakeholders, the primary takeaway is not an imminent global shortage, but a strategic transition into a market with thinning margins for error. This environment prioritizes those who secure capacity early, invest in efficiency to do more with less, and build flexible partnerships within the infrastructure value chain.

The convergence of the forecasts on key points—especially the tightening supply-demand balance—is a critical takeaway. It signals that current investment levels, while record-breaking, may still be insufficient to meet the wave of demand fueled by AI and broad digital transformation. The projected growth differential between data creation and physical capacity further highlights the urgent need for technological innovation in compute efficiency, not just in capacity expansion. For stakeholders, these results underscore the strategic importance of securing long-term capacity, investing in next-generation cooling and power efficiency, and closely monitoring the lead indicators of supply chain and energy grid constraints.

5. Conclusion

This study demonstrates the efficacy of grey forecasting as a strategic tool for navigating the high-growth, high-uncertainty digital infrastructure sector. By applying the DGM(1,1,α) model, we have generated robust projections for core market metrics, validating the model's accuracy against historical data and benchmarking its output against leading industry analysis. The central, managerially significant finding is not merely the confirmation of strong growth, but the identification of a critical shift in market structure: a pronounced compression of the global supply buffer. While absolute capacity continues to expand, the surplus relative to total demand is projected to shrink considerably, signaling a transition towards a tighter, less forgiving market environment.

This erosion of the relative safety margin has immediate implications for corporate strategy. For enterprise consumers of data center services, it heralds an end to the era of easily scalable, cost-flexible capacity procurement. The foreseeable future will be characterized by rising costs, longer planning horizons, and increased negotiation leverage for providers. Consequently, strategic planning must now prioritize long-term capacity security and supply chain resilience over short-term cost optimization. Proactive portfolio management, involving a mix of geographic diversification and forward-leasing, becomes a competitive necessity to mitigate operational risk.

For investors and operators, the converging trends point to a landscape where competitive advantage will be determined by efficiency and strategic execution. Capital allocation must increasingly favor assets and technologies that deliver higher power density and superior energy efficiency, as these attributes will command premium pricing and tenant loyalty in a constrained environment. Furthermore, the business model is evolving from pure asset ownership to one of integrated partnership, requiring operators to develop deeper technical and financial collaboration with major hyperscale tenants to secure large-scale, built-to-suit projects.

Ultimately, this analysis provides a quantitative foundation for a paradigm shift in managerial thinking. Treating digital infrastructure as a stable utility is no longer tenable. Instead, it must be recognized as a dynamic, strategic factor of production subject to tightening constraints. Success will depend on an organization's ability to incorporate forward-looking, non-linear forecasting into its strategic foresight, enabling proactive adaptation to the impending capacity crunch. The actionable insight is clear: in the coming decade, strategic foresight and early commitment will be far more valuable than reactive negotiation in securing the foundational compute resources that underpin modern enterprise.

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