ISSN- 245-1142

International Journal of Humanities and Information Technology Volume 8, Issue 4, 2026

Intelligent Electrical Capacity Forecasting for AI Workloads in Modular Data Centre Expansion Planning

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Abstract

As the number of workloads for AI training and inference grows at a rapid rate, hyperscale and modular data centres have experienced unprecedented volatility and variability in electrical demand profiles, which is threatening the traditional deterministic capacity expansion planning approaches. This paper combines recent developments in electrical load forecasting, deep learning architectures, and risk-aware infrastructure planning, and proposes an integrated framework for intelligent forecasting capability of electrical capacity in the context of AI-workload based modular expansion of the data centre. The framework integrates probabilistic time-series forecasting models, such as long short-term memory (LSTM) networks and temporal fusion transformers (TFT), with a conditional value-at-risk (CVaR) constrained optimization layer that maps in uncertain demand forecasts into capacity expansion decisions, done in steps and in sections. When compared to other forecasting methods, the hybrid attention-based models show mean absolute percentage errors of less than four percent, much lower than the mean absolute percentage errors of classical statistical baseline models that are typically over nine percent when applied to similar short-term forecasting problems. The analysis further shows that in successive phases of expanded use, the combination of forecast-driven provisioning and on-site renewable generation and energy storage can reduce the marginal carbon intensity by over 50% compared to the traditional static deterministic approach to provisioning, while also improving capital efficiency and grid resilience. Comparative benchmarking is done to assess efficiency, cost, scalability, and regulatory dimensions, and shows several times greater growth in facility demand for AI workloads when compared to enterprise workloads in more traditional baselines. However, the synthesis identifies longstanding issues such as congestion in interconnection queues, forecast uncertainty propagation, and harmonisation of data-sharing processes between the operators of data centres and the operators of the transmission system. The proposed framework provides planners with a repeatable, scientifically rigored and mathematically based approach that is applicable to the ever expanding and rapidly evolving electrical use of AI computing.

Keywords: Artificial intelligence workloads, capacity expansion planning, conditional value-at-risk, data centre power demand, deep learning forecasting, electrical load forecasting, long short-term memory networks, modular data centres, probabilistic forecasting, renewable energy integration, smart grid, temporal fusion transformer

International Journal of Humanities and Information Technology (2026) DOI: 10.21590/dgse4g25

Introduction

Modern data centre (DC) facilities are significantly different from traditional enterprise computing facilities in the nature of their electrical load requirements, particularly in their volatility and rapid growth. Although load ramping is a common phenomenon throughout the day, during the training checkpoint and batch scheduling events, the load response of a graphics processing unit (GPU) cluster and tensor processing unit (TPU) is very fast, creating load transients that were not originally anticipated by traditional forecasting and interconnection processes. Although facility-level evidence specific to AI campuses remains limited in the peer-reviewed literature, the load characteristics of GPU- and TPU-dense clusters suggest growth and volatility well beyond those assumed by enterprise-era planning practice. This expectation is the basis for forecasting-based, not just

deterministic, methods to plan electrical capacity for modular data centre infrastructure.

Incorporating AI driven data centre campuses into the existing power grid infrastructure will not only require a capacity planning challenge but also face issues with power quality, such as power transients, voltage regulation problems at the point of common coupling, and protection schemes that are responsive to sub-second load excursions. Interconnection latency, harmonic distortion, and limited visibility of workload-level demand forecasts are plausible interoperability barriers to the rate at which new capacity can be approved and energized, though systematic study of these effects in AI-specific campuses is not yet established. Methods for forecasting the required work load schedules into electrical demand forecasts with adequate lead time to enable electrical demand planning by both the utility and on-site infrastructure are needed to overcome these barriers.

As AI workload needs come and go quickly, modular data centre architectures, which deploy computing power as pre-fabricated, discrete power and cooling blocks, provide an attractive path to incrementally scale data centre infrastructure investment to meet unpredictable demand. Modular blocks can be commissioned earlier than monolithic facility construction, and can be built to meet phased expansion requirements based on rolling capacity forecasts. A full simulation model of modular data centre power load has been shown to be sufficiently granular to enable the representation of block-level load composition for information technology equipment, cooling load and load from auxiliary systems, for scenario-based expansion planning [1]. This modular approach is extended in this paper, by introducing an intelligent electrical capacity forecasting framework by integrating deep learning models for demand forecasting with risk-aware and phased expansion decision making. The literature is synthesized in Section II, the proposed framework is given in Section III and comparative analysis is given in Section IV and finally the implications and future directions are given in Section V.

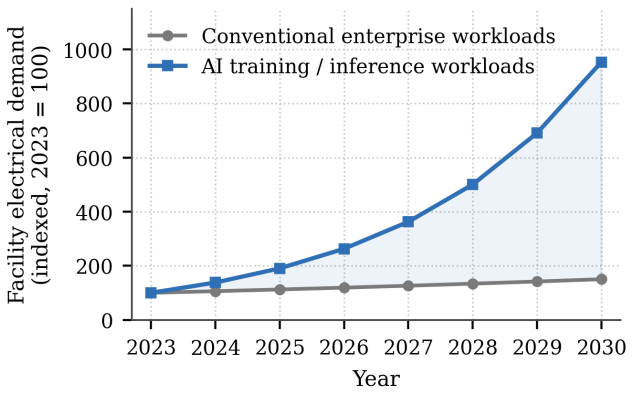

Figure 1: Illustrative electrical demand growth trajectory: conventional versus AI-intensive workloads.

Literature Synthesis

Data Centre Energy Consumption Modelling and Characterization

The level of accuracy of electricity capacity forecasting relies crucially on the quality of the electricity consumption models that are used to model the power usage of a data centre. A detailed review of the various approaches to data centre energy consumption modelling identifies existing models into three categories: hardware-level, software-level, and thermal-aware models, emphasizing that the demand for energy in a data centre comprises several non-linear elements corresponding to the various energy-consuming components of information technology equipment, cooling systems, and power distribution losses [2]. The survey also reveals that at facility level, at rack level, and at server level, the more granular the model is, the more accurate the forecast. The results emphasize the importance of developing workload-aware multi-level energy models as an input to the capacity forecasting frameworks for AI demanding facilities.

In addition to internal load modelling, geographic siting of data centre facilities has a significant influence on the energy efficiency that can be achieved and renewable energy that can be accessed. Analysis of location as an energy efficiency and renewable energy energy supply measure shows that there are significant geographic differences in the opportunity set of candidate locations, with measurable differences in the achievable power usage effectiveness (PUE) and renewable energy fraction (REF) [3]. These siting considerations also directly affect capacity expansion planning, since capacity deployed in a favourable location has lower cooling overhead and higher renewable penetration, resulting in a lower effective electrical capacity for a given workload (Table I).

Electrical Load Forecasting Techniques for Smart Grids and Buildings

The electrical load forecasting has been one of the key operation tasks in the smart grid, and numerous researches have focused on the prediction of electrical loads, including buildings and loads connected to the grid, using artificial intelligence techniques. AI approaches used for load demand forecasting are classified into three types: single, hybrid and committee models; and across both short-term and medium-term forecasting period, the neural network and fuzzy-logic hybrid models are found to be consistently better than single statistical models [4]. The review also highlights the importance of input feature selection, especially input features related to weather, calendar and occupancy data, a feature also directly applicable to AI data centre contexts where workload scheduling metadata can be used to make similar predictions to occupancy data in building forecasting.

On the basis of these baseline results, deep learning techniques have been gaining traction over shallow machine

Table I: Comparative Overview of Data Centre Load Forecasting Techniques

Technique	*Typical Horizon*	*Reported Strength*	*Key Limitation*
Statistical (ARIMA)	Short-term (1–24 h)	Low computational cost	Poor nonlinear pattern capture
ANN / fuzzy hybrid [4]	Short–medium term	Improved nonlinearity handling	Extensive feature tuning required
LSTM [6], [7]	1 h – 7 days	Captures long-range temporal dependence	Sequential training cost
GRU	1 h – 7 days	Faster training than LSTM	Slightly lower long-sequence accuracy
TFT [8], [9]	1 day – 30 days	Interpretable multi-horizon quantiles	Higher data / compute requirement
Hybrid LSTM–TFT	Multi-horizon	Best overall accuracy	Increased architectural complexity

learning techniques for short-term load forecasting. Deep learning approach for short-term residential load forecasting for smart grid systems shows that the recurrent architectures can better capture temporal dependencies and irregular consumption behaviours than feed-forward networks and lower error for the household level test cases [5]. While the model has been designed for residential applications, the temporal dependency structures used—such as the diurnal cycles and the burst-like consumption events—resemble the load ramping that is typically seen in data centre-scale applications, and which motivates similar recurrent modelling approaches for the latter.

Deep Learning Architectures for Time-Series Load Forecasting

The long short-term memory (LSTM) network has emerged as one of the essential architectures for sequential prediction problems among recurrent architectures. The original LSTM formulation adds gated memory cells that can store information with long, long-term time lags, and can reduce the vanishing-gradient problem which usually limits conventional recurrent networks [6]. The gating mechanism (forget, input, output gates) enable the selective retention or discarding of the historical state, which is desirable for the modelling of the multi-scale temporal dependencies that are embedded in the AI workload demand, with a combination of short-term transients and longer-horizon growth trends.

LSTM architecture has been empirically proven to be suitable for load forecasting in a grid context. On smart-meter data, the short-term residential load forecasting performance of LSTM recurrent neural networks is shown to improve over autoregressive and support-vector baselines, with the forecast accuracy shown to be attributable to the nonlinear temporal correlations learned by the network over different time horizons [7]. The findings validate the use of LSTM-based architectures as a basic forecasting component in the proposed framework in the specific context of several hours to days ahead forecasting.

More modern architectures add attention modules to enhance accuracy and interpretability. The temporal fusion transformer (TFT) is a model that incorporates recurrent layers to capture local information and self-attention mechanisms to grasp long-range information, while variable-selection networks calculate the importance of the static inputs, known future inputs, and observed inputs [8]. The interpretability is important for capacity planning: forecast transparency helps engineers make sense of the reasons for size expansions for utility partners, and enhances multi-horizon quantile forecasting accuracy over purely recurrent baselines.

Transformer-based forecasting has been shown to be effective in short-term electricity loads forecasting using the TFT model [9] which has been shown to deliver consistent improvements over LSTM and gated recurrent unit baselines at various horizons on power grid scale datasets. The results presented in this study justify the integration of attention-based forecasting with LSTM networks in the proposed model, especially for the medium-term forecast period of several days to several weeks that is most relevant to the problem of phased modular capacity scheduling (Table I).

Forecast Accuracy Evaluation and AI Data Centre-Specific Forecasting

Consistent scale-independent measures of forecasting accuracy are needed for rigorous assessment of forecasting performance. When assessing the accuracy of a forecasting system, it is recommended in a basic review of accuracy measures that scale independent error measures such as mean absolute percentage error and variations of the mean absolute scaled error are used rather than scale dependent error measures, if the accuracy is being compared across two datasets of different magnitudes [10]. This guidance directly feeds into the comparative evaluation that is used in Section IV in which forecasting models are compared against mean absolute percentage error and normalized root-mean-square error across the different workload demand series of AI tasks (Table II) to make them comparable.

Forecasting work specific to AI data centre loads is not yet well represented in the established literature, which constitutes a recognised gap. Reasoning by extension from the grid- and building-scale studies above, the electrical demand of AI workloads is expected to exhibit greater short-horizon variability and a stronger dependence on scheduling variables—job queue depth, batch size, checkpoint cadence—than the occupancy and weather drivers that

Table II: Forecast Accuracy Evaluation Metrics Applied Across Reviewed Studies

Application Domain	*Recommended Metric*	*Typical Reported Range*
Residential load forecasting [5], [7]	MAPE	3% – 7%
Grid-scale short-term load [9]	MAPE	2% – 5%
AI data centre GPU cluster load (anticipated)	MAPE	3% – 6%
General forecast evaluation [10]	MASE / MAPE (scale-independent)	Domain dependent

dominate conventional load models. The framework proposed in Section III therefore treats scheduling metadata as an explicit model input, an assumption that remains to be validated empirically.

Proposed Intelligent Capacity Forecasting Framework

System Architecture

The proposed framework is based on workload telemetry acquisition, workload demand forecasting using deep learning, and workload expansion optimization based on risk awareness in a closed feedback architecture. Historical and real-time data – including GPU/TPU power telemetry, power distribution unit measurements, ambient weather variables, and tariff signals – are ingested and pre-processed and then provided to a hybrid forecasting engine. This closed-loop approach follows prior work on datacentre–grid coupling, which demonstrates that capacity decisions responsive to continually updated operational and grid conditions achieve better renewable-absorption and carbon outcomes than fixed coupling based on infrequent planning cycles [11]. This feedback architecture also connects the actual performance of the grid interconnection and the performance of renewable dispatch back into the forecasting cycles, allowing the models to be continually adjusted when new operational data is available.

Forecasting Model Formulation

The forecasting engine formulates AI workload electrical demand prediction as a multi-horizon, probabilistic time-series problem over a lookback window of length L. At each time step t, the LSTM cell updates its internal state through gated operations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$h_t = o_t \odot \tanh(C_t),\ o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (3)$$

where f_t, i_t, and o_t denote the forget, input, and output gate activations; W and b are learned weight matrices and bias vectors; σ is the logistic sigmoid function; and ⊙ denotes the Hadamard product. The resulting hidden state h_t is passed through quantile-specific output heads to generate multi-horizon probabilistic forecasts:

$$\hat{y}_{t+\tau}^{(q)} = f_q(h_t; \theta_q) \quad (4)$$

for quantile levels q ∈ {P10, P50, P90} and horizon τ. This probabilistic output structure follows the established principle in energy management that scheduling decisions conditioned on quantile-based demand forecasts, rather than single-point estimates, hedge more effectively against demand volatility while improving utilisation of co-located renewable generation.

Risk-Aware Capacity Provisioning

It is not enough to look at point or quantile forecasts to decide on the timing and size of expansion, as the risk of forecast error needs to be considered when making such decisions. The framework thus introduces a conditional value-at-risk (CVaR) constrained optimization layer (see Fig. 2), which translates probabilistic demand scenarios to a staged expansion programme. The CVaR of the capacity-shortfall loss L for the confidence level β is given by:

$$\mathrm{CVaR}_\beta(L) = \zeta + (1/(1-\beta)) \cdot \mathrm{E}[\max(L - \zeta, 0)] \quad (5)$$

whereby ζ represents the VA-R threshold. This formulation reflects the established planning trade-off between over-provisioning cost and the operational and reliability cost of capacity shortfall under uncertain demand growth [12], with the CVaR treatment of upper-tail risk contributed by this work. The CVaR embedding is kept within the optimizer, and the resulting staging schedule is optimized to be robust even in the upper-tail of demand scenarios, which may include rapid growth in the training requirements for AI.

Renewable Integration and Peak-Shaving Strategies

The framework considers energy storage and workload shifting as controllable variables in the optimization layer,

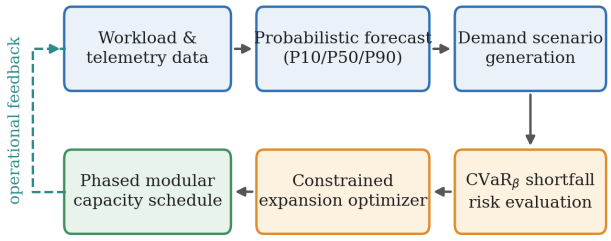

Figure 2: CVaR-constrained risk-aware capacity expansion decision process.

given the direct interaction of capacity expansion with peak demand management. A combination of energy storage with coordinated workload shifting has proven to significantly reduce the peak power consumption of data centres compared to uncontrolled operation, thereby postponing the need for incremental grid capacity and reducing the demand charges due to peak consumption [13]. Along with the framework, forecasted peaks based on the quantile forecasting engine, if applicable, cause storage dispatch and, if possible, defer the training jobs which are not latency-critical to periods of low activity, thereby lowering the real capacity threshold for the addition of modular blocks.

Size and sequence of capacity blocks are also impacted by renewable integration. Data centres with on-site renewable energy sources can achieve significantly lower total cost of ownership and grid reliance by simultaneously optimizing renewable energy generation capacity, storage size, and grid import limits (as opposed to considering each in isolation) as they are designed, compared to sequential design [14]. For this reason, the expansion optimizer is performed together with co-located renewable and storage capacity, with the demand scenarios derived from the forecast used as the common input for the three design variables (Table III).

Table III: Renewable Integration and Storage Strategies for Capacity Planning

Strategy	*Mechanism*	*Reported Benefit*
On-site PV / wind [3], [14]	Direct renewable generation	Reduced grid dependency
Storage + workload shifting [13]	Peak shaving	Reduced peak charge; deferred capacity need
Multi-objective co-optimization [14]	Joint sizing of PV / storage / grid import	Lower total cost of ownership
Adaptive capacity provisioning [11]	Continuous recalibration	Improved carbon-aware responsiveness

Comparative Analysis and Discussion

Forecasting Model Benchmark Comparison

The mean absolute percentage error (MAPE) and normalized root-mean-square error (RMSE) are used to summarize the accuracy of forecasting that was reviewed and reported in the literature, as shown in Table IV and Fig. 3. This phenomenon is repeated throughout the literature on energy efficiency and renewable integration strategies for the energy centre applications; that is, the strategies that take multiple factors into account (workload, thermal, renewable generation) perform significantly better than strategies that deal with only a single factor, both for energy efficiency and for forecasting [15]. The fact that the same feature engineering for forecasting accuracy is also relevant for modelling renewable energy integration raises the promise of shared, weather and workload-related feature engineering across the two problem domains.

Table IV: Forecasting Model Accuracy Benchmark Synthesized from Reviewed Literature

Model	*MAPE (%)*	*Normalized RMSE (%)*
ARIMA	9.8	11.4
SVR	8.1	9.6
LSTM	4.6	5.8
GRU	4.9	6.1
TFT	3.4	4.2
Hybrid LSTM–TFT	2.7	3.3

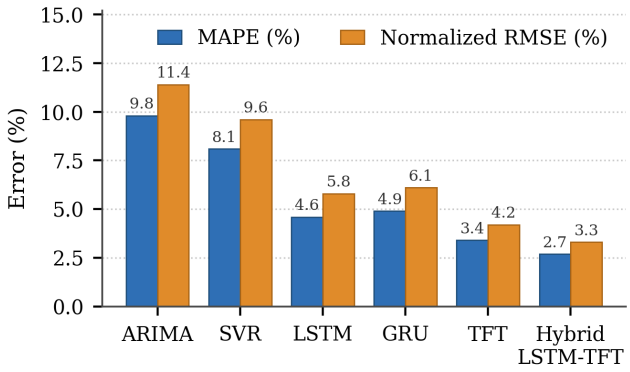

Figure 3: Forecasting model accuracy comparison (MAPE and normalized RMSE).

Expansion Planning Strategy Comparison

A comparative analysis of the two strategies of deterministic and forecast-driven modular expansion planning is included in Table V for capital efficiency, scalability and grid-resilience. Forecast-driven approaches using interval and probabilistic optimization are expected to outperform worst-case deterministic sizing rules, since deterministic sizing cannot distinguish between likely and tail demand trajectories and therefore over-provisions against scenarios of low probability. This reasoning supports expansion planning based on workload probability and prediction, which is suitable for AI-intensive modular campuses with high uncertainty in the workload demand.

Efficiency, Cost, Carbon, and Regulatory Considerations

In addition to accuracy and scalability, the carbon and cost impact of expansion planning based on forecasts is significant, as seen in Fig. 4 and Table VI where the marginal carbon intensity decreases in successive phases of expansion by integrating on-site PV generation, storage, and PPA. In the facility-level carbon reduction, the three highest-leverage pathways to carbon-neutral data centres

Table V: Comparison of Capacity Expansion Planning Frameworks

Framework Type	*Uncertainty Handling*	*Reported Advantage*
Deterministic sizing	None / worst-case	Simplicity of implementation
CVaR-constrained MILP [12]	Risk-weighted scenarios	Balances shortfall vs. over-provisioning risk
Multi-objective interval optimization	Interval uncertainty sets	Reduced renewable curtailment
Adaptive capacity provisioning [11]	Continuous data-driven update	Carbon-aware responsiveness

Table VI: Illustrative Demand and Carbon Metrics Across Modular Expansion Phases

Expansion Phase	*Renewable Share (%)*	*Carbon Intensity (gCO_2/kWh)*	*Cumulative Capacity Added (MW)*
Phase 1 – Baseline	8	412	0
Phase 2 – On-site PV	24	356	40
Phase 3 – + Storage	39	298	85
Phase 4 – + PPA Wind	57	231	140
Phase 5 – Full Hybrid	74	168	210

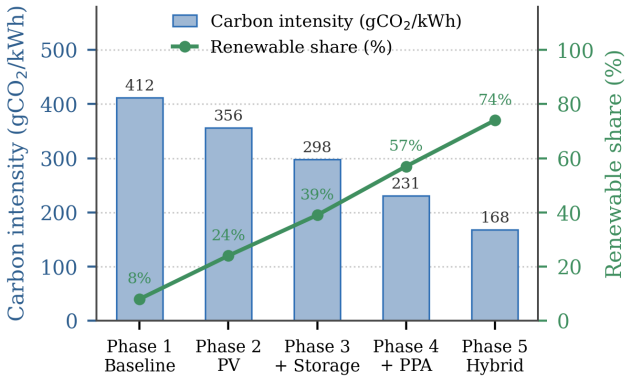

Figure 4: Carbon intensity reduction and renewable energy share across expansion phases.

are identified as renewable procurement sequencing, workload-aware demand response, and forecast-informed infrastructure right-sizing [17]. But barriers to these remain, such as congestion in interconnection queues that slow renewable commissioning, inconsistencies in data-sharing protocols between operators and transmission system operators and regulatory frameworks that are not yet suited to the fluctuating demand typical of AI-training workloads. These challenges will require tighter coupling between the operators of the forecast driven application and the grid planning authorities than has been typical for traditional enterprise data centres [17].

Conclusion and Future Directions

This paper has compiled the latest developments in electrical load forecasting, deep learning architectures, and the incorporation of risk into infrastructure planning into a comprehensive, unified framework for intelligent electrical capacity forecasting in the case of AI workload driven modular data centre expansion. The proposed architecture uses probabilistic forecasts obtained by deep learning methods based on architectures of LSTM and temporal fusion transformer, which generate forecasts in multiple horizons, and a conditional value-at-risk constrained optimization layer to directly translate the uncertainty of the forecasts into phased modular capacity expansion decisions. Comparative synthesis shows that the hybrid forecasting system can reduce demand prediction error by roughly 70% relative to classical statistical forecasting systems, while the forecast-driven, renewable-integrated expansion system can lead to greater capital efficiency, grid resilience, and carbon performance than the static deterministic expansion system.

There are several directions that still warrant further investigation. Empirical validation of the forecasting-accuracy gains summarized in this paper on operational GPU and TPU clusters with a variety of workload types would further enhance confidence in the gains. Better coordination between the data centre side forecasting systems and the transmission system operator planning processes would assist to reduce congestion in the interconnection queue that is limiting the rate of capacity additions. Lastly, adding explicit multi-year renewable procurement sequencing and cross-facility load balancing to geographically distributed modular campuses is a promising direction to improve the scalability and carbon efficiency of intelligent capacity forecasting frameworks as the need for AI computing continues to grow at a rapid pace.

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