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# Organization I want to improve the System for

## Dar al-Hadassah

Dar is one of the most famous companies that provides design, planning, engineering, and project management for buildings, cities, and many more.

### Dar History

Dar started a specialized engineering firm with four professors from the American University of Beirut to meet the rising regional demand in 1956. And it continued it success until nowadays, which it has over 54 offices in the Middle East, Africa, Asia, and Europe.

# Dar’s AI system

Dar Al-Handasah uses a **Digital Solutions & Engineering Services AI platform**, which is an AI productivity platform that uses advanced analytics, algorithms, and automation at the planning, design, and operation levels in an engineering project’s life cycle. The platform gathers data from various sensors and IoT devices, as well as from the building management systems, to enable fault detection, predictive maintenance, and performance tuning. The AI capabilities enable Dar to enhance project delivery by driving operational efficiency, reducing costs, and enabling informed decisions on complex buildings and infrastructure projects.

## Core component of the system

|  |  |
| --- | --- |
| Component | Function |
| Data Collecting Layer | Collects the data from sensors, IoT devices, BMS (Building Management Systems), and SCADA systems. |
| Data Integration & Management | Standardizes and stores data using cloud and local platforms for interoperability. |
| AI & ML Analytics | Machine learning models are applied to perform fault detection, predictive maintenance, anomaly detection, and optimization. |
| Visualization & Automation Tools | Custom dashboards and digital twins to give stakeholders the ability to interact with AI insights and automate control systems. |

# Proposed Enhanced AI System for Dar Al-Handasah

## Region-Adaptive AI Models

Most of the Dar’s models are trained on datasets from specific regions. But building behavior and energy are changing a lot across geographic regions due to:

* Climate
* Building materials
* Culture using patterns
* Government energy policies

So this gives weak performance when applied to the middle in different regions, and training a model from scratch for every region will be expensive. So my solution is to make an AI adaptable to each region or building automatically.

### How It Works

Instead of training a new model from scratch for every region,transfer learning allows you to take a pre-trained model and fine-tune it using smaller, region-specific datasets. Example:

* Base Model: The model will be trained on a large, diverse dataset from various smart buildings
* Region-Specific Fine-Tuning: We retrained the model on a small set of recent data from a specific city or building.
* Deployment: The updated model will have the ability to predict and optimize based on both global knowledge and local adaptation.

### Technical strategy

1. Implement a regional data ingestion pipeline to automatically fetch recent local sensor data (occupancy, humidity, temperature).
2. Utilize automated fine-tuning algorithms.
3. Track performance and utilize continuous learning to continuously update the model as building usage evolves seasonally or behaviorally.
4. Add a model confidence measure to alert when the predictions of the system decrease in accuracy and retraining is required.

### Comparison Between the Dar system and my system

|  |  |  |
| --- | --- | --- |
| Feature/Aspect | Existing AI System | Proposed Region-Adaptive AI System |
| Model Training Approach | Locally trained or static AI models per building/region | Transfer learning with base models fine-tuned to local data |
| Adaptability | Limited; manual retraining needed for new locations | Automatic domain adaptation to new climates and usage patterns |
| Data Requirements | Requires large datasets per building/location | Requires smaller local datasets; leverages prior knowledge |
| Scalability | Low; each deployment requires significant effort | High; deployable across multiple buildings/regions efficiently |
| Model Update Mechanism | Periodic manual retraining | Continuous learning with real-time feedback integration |
| Handling of Regional Variations | Poor generalization across different climates or cultures | Explicitly designed for regional variation with transfer learning |
| User Feedback Integration | Typically, none or limited | The occupant feedback loop enables dynamic comfort adjustments |
| Operational Efficiency Gains | Optimized per building, but limited transferability | Greater overall energy efficiency by adapting to local conditions |
| Maintenance Effort | High requires expert intervention for each site | Lower, automated fine-tuning reduces maintenance workload |

# Articles help me to gain my understand

## 1. Energy predictive Models with limited data using Transfer

**Paper**: [*Energy Predictive Models with Limited Data using Transfer Learning* – Hooshmand & Sharma, 2019](https://arxiv.org/abs/1906.02646)

**1. Summary**

This article shows a deep learning-based approach for forecasting energy consumption in scenarios where limited historical data is available. This article uses **Convolutional Neural Networks (CNNs)** combined with **Transfer Learning** to improve prediction performance. The methodology involves pretraining models on large, data-rich buildings and then transferring the knowledge to smaller ones, significantly reducing the need for extensive training data.

**2. Key Ideas & Information**

* The main AI model is a **Convolutional Neural Network (CNN)** used for time series regression.
* How to apply **Transfer learning** by pretraining on a source building that has a lot of data, then fine-tuning for a target building with minimal data.
* The method is validated on public datasets.
* The model gives a High improvement in forecast accuracy, even when used in a low-data context, over traditional ML and deep learning models trained from scratch.

2. **Learnings & Insights**

**Benefits for the system:**

* enhance energy forecasting accuracy in buildings with limited historical data.
* Reduces the time and cost of training deep learning models from zero.
* Give us **scalable deployment** across different buildings in a smart city environment.

**Disadvantages:**

* The pretrained model may not always generalize well if the source and target buildings are very significantly different in characteristics.
* It still needs **an amount of labeled data** for fine-tuning on the target building.
* CNNs may be less effective at capturing long-term dependencies compared to models like LSTMs or Transformers.

**3. How Information Will Be Used**

This paper gained my understanding of AI modeling techniques (CNNs, Transfer Learning), which are effective in rare data in energy prediction. This is relevant for organizations that want to implement smart energy systems across multiple buildings with low data availability. It highlights the importance of model reusability and cross-building generalization, which can be useful in reducing costs and enhancing decision-making in facility management.

**4. Survey/Interview Questions**:

* How much past energy use information do you usually have for each building? Do you have any problems when there isn’t much data?
* Would your team be open to using ready-made AI models (trained on other buildings) to help predict energy use better in buildings where you don’t have much information?

2. Transfer Learning in Deep Learning Models for Building Load Forecasting: Case of Limited Data  
  
Paper: [Link to paper](https://arxiv.org/abs/2301.10663)

**1. Summary**  
This paper shows the application of deep learning models based on transformers in building energy load forecasting under the condition of rare historical data. The authors show that transfer learning is a useful way to increase forecast accuracy by pretraining models on big datasets and subsequently fine-tuning them on small ones through experiments they show that it leads to an improvement in prediction accuracy by up to 56.8% compared to models trained from scratch.

**2. Key Ideas & Information**

* This article used a transformer-based model that was trained on buildings that have a lot of data and fine-tuned on the limited data.
* It shows that **transfer learning** improves forecasting in low-data scenarios.
* Their model achieves a **56.8% improvement** in accuracy over conventional training approaches.
* The method is evaluated using standard public datasets.
* Emphasis is placed on how knowledge transfer can generalize across different building types and conditions.

**3. Learnings & Insights**

**Benefits:**

* How to use Substantially to boost model accuracy when we have limited training data available.
* Makes high-performance AI accessible for smaller organizations or facilities without rich historical datasets.

**Disadvantages:**

* Requires access to a well-pretrained source model which is hard to do in most companies.
* We may challenge overfitting if the target and source are very differennt domains.

**4. How Information Will Be Used**  
This article is relevant to my research on region-adaptive AI systems, especially in domains where data availability varies significantly across locations. It showed me the practical value of using transformer architectures and transfer learning to overcome data scarcity, and how such models can be adapted to new settings with minimal fine-tuning. This insight can guide the design of flexible AI systems that generalize well across regions.

**5. Survey/Interview Questions**

1. Has your organization tried using AI tools that adjust to each building’s or area’s energy use patterns?
2. Would you be open to using AI systems that learn from other buildings or regions to help improve your energy use predictions?

3.TgDLF2.0: Theory‑Guided Deep Learning for Electrical Load Forecasting via Transformer and Transfer Learning – Gao et al., 2022  
paper: [arXiv:2210.02448](https://arxiv.org/abs/2210.02448)

**1. Summary**  
This article presents **TgDLF2.0**, a hybrid deep learning framework that combines **Transformers** and **Transfer Learning** to improve **short-term electrical load forecasting**, especially in scenarios with limited or sparse data. The model incorporates **physics-based domain knowledge** into its deep learning architecture, enabling faster convergence, better generalization, and higher forecasting accuracy. It is particularly designed for energy systems with limited access to extensive historical data.

**2. Key Ideas & Information**

* **Core AI Technique**: Transformer-based model optimized for time-series forecasting.
* **Theory-Guided Component**: The model integrates known physical laws and energy load principles into the learning process.
* **Transfer Learning**: Models are pretrained on large, rich datasets and fine-tuned on target datasets with limited samples.
* **Improved Efficiency**: The hybrid framework achieves faster convergence and higher accuracy than traditional models.
* **Experimental Results**: Demonstrated superior performance over baselines such as LSTM and other non-guided DL models.
* **Application Focus**: Particularly useful for utilities managing smart grids in regions with incomplete historical data.

**3. Learnings & Insights**

**Benefits:**

* Effectively addresses the challenge of **data scarcity** in energy forecasting.
* Embeds **domain knowledge**, improving interpretability and reducing overfitting.
* **Faster training** and deployment via pretrained models and guided learning.
* Scalable to multiple regions or buildings with minimal additional data.

**Disadvantages:**

* Requires **careful tuning** to balance theoretical constraints and learned patterns.
* **Transferability** may be reduced if target domains significantly deviate from the source.
* **Transformer models** can be computationally intensive compared to simpler architectures like LSTM.

**4. How Information Will Be Used**  
This paper helped me understand how **hybrid AI models** combining **theory, Transformers, and Transfer Learning** can be used to improve forecasting accuracy in **data-constrained environments**. It provides insights into designing robust AI systems for smart energy management, where historical data availability varies across regions or buildings.

**5. Survey/Interview Questions**

1. How often do you have problems because there isn’t enough past energy data when predicting energy needs?
2. Would your organization be willing to use AI models that were trained using data from other places to help improve your local energy forecasts?

4.GenTL: A General Transfer Learning Model for Building Thermal Dynamics – Raisch et al., 2025

Paper: [arXiv:2501.13703](https://arxiv.org/abs/2501.13703)

**1. Summary**  
This article introduces **GenTL**, a universal transfer learning framework for modeling **building thermal dynamics** using **Long Short-Term Memory (LSTM)** networks. The model is pretrained on a large dataset containing thermal data from **450 diverse buildings**, and then **fine-tuned** on individual target buildings. GenTL achieves a **~42% reduction in RMSE** compared to traditional training from scratch, showcasing strong generalizability and data efficiency in forecasting indoor temperatures and thermal behavior.

**2. Key Ideas & Information**

* **Model Type**: LSTM (Long Short-Term Memory) network optimized for time-series data involving temperature and HVAC dynamics.
* **Transfer Learning**: GenTL is trained on 450 source buildings and then fine-tuned for new buildings using limited local data.
* **Performance**: Achieves ~42% lower RMSE compared to training models individually per building.
* **Efficiency**: Greatly reduces time and data required for deploying thermal prediction systems in new or existing buildings.
* **Target Use Case**: Smart building climate control, HVAC optimization, and energy-efficient management.

**3. Learnings & Insights**

**Benefits:**

* **Strong generalizability** across diverse buildings with minimal customization.
* Reduces training costs and data collection efforts for new building deployments.
* Supports large-scale deployment in **smart city infrastructure** with mixed building types.
* Can improve comfort and energy efficiency through better thermal prediction.

**Disadvantages:**

* Performance depends on **similarity between source and target buildings** (e.g., insulation, HVAC systems).
* Fine-tuning still requires some labeled thermal data, which may be unavailable in old buildings.
* LSTM models may struggle with **long-range dependencies** or sudden environmental changes compared to newer architectures like Transformers.

**4. How Information Will Be Used**  
This paper helped me understand how **pretrained LSTM models** can be scaled to work across many buildings, offering a viable solution for **data-scarce thermal modeling**. It demonstrates the value of universal models in **smart building applications**, especially in reducing manual work and enhancing operational scalability in thermal prediction tasks.

**5. Survey/Interview Questions**

1. How do you currently predict indoor temperature and energy use in your buildings?
2. Would it be helpful to use one AI model, trained on many buildings, to quickly predict temperature in your facilities?

5.Powering Electricity Forecasting with Zero-Shot Transfer Learning – Kamalov et al., 2024  
Paper [Energies Journal](https://www.mdpi.com/1996-1073/17/3/626)

**1. Summary**  
This article presents a novel approach to electricity generation forecasting using **N-BEATS** deep learning architecture combined with **zero-shot transfer learning**. The proposed method enables accurate forecasting in new target domains without any retraining on target-specific data. This results in fast, efficient, and scalable electricity forecasting solutions that can be deployed immediately to new regions or grids with little historical data.

**2. Key Ideas & Information**

* Uses the **N-BEATS** architecture, optimized for interpretable and accurate time-series forecasting.
* Implements **zero-shot transfer learning** to forecast electricity generation in **unseen domains without retraining**.
* Reduces computational costs and deployment time drastically compared to traditional transfer learning methods.
* Evaluated on multiple datasets, showing comparable or better accuracy than retrained models.
* Targeted for electricity generation forecasting across grids with limited or no historical data.

**3. Learnings & Insights**

**Benefits:**

* **Zero-shot learning** enables immediate deployment to new domains without collecting labeled data.
* **High accuracy** maintained despite lack of target-specific retraining.
* Reduces computational and operational overhead.
* Supports scaling forecasting models across regions with different characteristics.

**Disadvantages:**

* May underperform if the target domain is extremely different from source domains in data distribution or generation patterns.
* Zero-shot approaches depend heavily on the diversity and representativeness of the pretrained source models.

**4. How Information Will Be Used**  
This paper helped me understand the potential of **zero-shot transfer learning** combined with advanced architectures like N-BEATS for **fast, scalable forecasting** in electricity systems. It highlights a promising pathway for utility companies or energy providers to deploy predictive models quickly across diverse and data-scarce grids.

**5. Survey/Interview Questions**

1. How important is it for your organization to quickly use forecasting tools in new areas without having to train them again?
2. What problems do you have when collecting and organizing electricity data for new places or grids?

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