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Publisher's Home Page: https://www.svedbergopen.com/
Research Paper Open Access

Energy Consumption Prognosticate In Built Environment Using GAN Approach

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Abstract
Building accurate and robust models for forecasting energy consumption is a key objective in managing and operating smart buildings. While previous research has explored various load prediction techniques, the combined impact of data augmentation and machine learning on energy forecasting remains underexplored. To address this, the present study introduces a novel ensemble-based approach enhanced with Generative Adversarial Networks (GANs) for predicting energy usage in large commercial buildings.The proposed framework integrates multiple base models using a stacking ensemble method, while GANs are employed to learn the underlying data distribution and generate high-quality synthetic samples to augment the training dataset. This enriched dataset enables the model to train on a broader spectrum of scenarios, thereby improving robustness and generalization.The experimental evaluation investigates the effectiveness of the approach by employing three different GAN variants and measuring performance with metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Variation of RMSE (CV-RMSE). Results highlight the practical potential of the proposed method, demonstrating its capability to deliver accurate energy consumption forecasts for real-world applications in smart building management.

Keywords: GAN, energy consumption, forecasting, predictive, analytics, built environment, smart city, Sustainable Development Goals.

1. Introduction:

In the terrain of resilient Cities, the requirement for smart strategies to effectively conduct and synchronize divergent energy supply, technologies of conversion, and applications for demand are well recognized. The widespread deployment of detectors, combined with embedded computationalalgorithms of intelligence, presents a promising approach to addressing the technical challenges of integrating energy systems. However, challenges remain, including the need for methods that can navigate complicated networks of stakeholders with conflicting objectives, while buildingplan and functional decisions across various features and timeframes.

The driving force behind newand advance industries is energy, generating the great value for our era. Over the past few decades, significant transformations have been fuelled by technological advancements in areas such as cell cyberspace, 5G, deep learning, and smart cities. The innovations have enhanced connection between individuals and various organizations, that has improved the productivity of manufacturing, and accelerated portage and handling. However, these benefits have also led to a significant increase in consumption of energy and CO2 emissions, emphasizing the need for accurate and resilient energy prediction models.

Thisexplores recent developments through the sector of smart energy, concentrating on the various methodologies in main application departments and citing relevant examples of implementations. It then highlights the primary issues facing the sector today and outlines possible future directions. Furthermore, it provides a comprehensive outlook of a designdeveloped for the EU H2020 funded Sharing Cities project, offering insights into the various stages of model and manage the hierarchies involved.

The goal of our study mainly captures the running state of knowledge engineeringin the administration of smart energy and insights are provided into overcoming existing barriers. The first section offers an overall review of the study, followed by a detailed investigation of various papers, the methodology employed, and the conclusions drawn from our research.

2. Background:

This research introduces a novel method for enhancing energy consumption forecasting in large commercial complexes through a Generative Adversarial Network (GAN)-augmented ensemble model. While previous studies have investigated various predictive techniques, the combined effect of data augmentation and meta-learning approaches in energy forecasting has received limited attention.

The proposed framework employs an ensemble architecture that integrates five individual models using a stacking strategy, while a GAN is utilized to generate high-quality synthetic samples from the original dataset. These enriched samples expand the training data and improve the robustness of the predictive model.

To assess effectiveness, the study experiments with three GAN variants and evaluates performance using a threefold set of metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Variation of RMSE (CV-RMSE).

2.1 GAN Architecture:

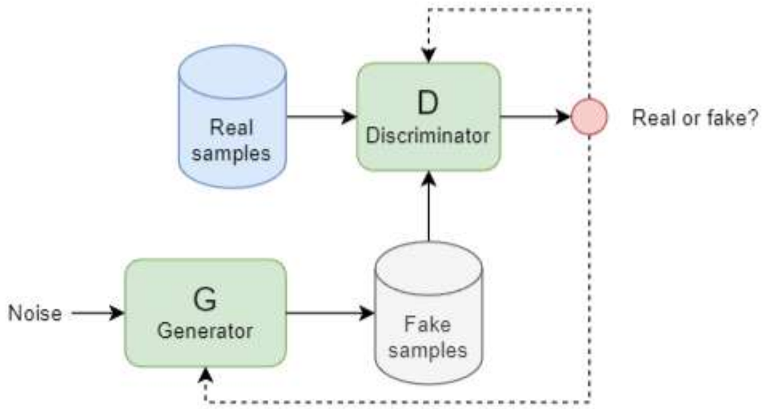

Figure 1 : GAN Architecture

A Generative Adversarial Network (GAN) is a prototype that learns the underlying dispersal of samples in a dataset that is provided. In our research, here we utilize a GAN-driven reinforce method to create new training samples that closely mirror, or even replicate, the distribution found in the original dataset. It enables the enhancement of fault detection capabilities to encompass fault diagnosis, identification, and prognosis[8].

In this framework, both the generator and discriminator operate under adversarial conditions. The generator creates synthetic images aimed at tricking the discriminator, while the adversarial attacker alters real images to confuse the discriminator[32].

Statistical discrepancies highlight the object classes that a GAN fails to generate. Next, we provide direct visualizations of these missing object classes. Specifically, we examine the differences between individual images and their corresponding approximate reconstructions generated by the GAN [33].

To explore the possibility of a causal relationship, we introduce a regularization technique called "Jacobian Clamping," which disciplines the statecount of the generator's Jacobian. This technique consistently improves the average scores across nearly all datasets tested, while significantly reducing the variance between runs, addressing one of the major criticisms of GANs [34].

Investigations were steered to show the strong performance of MAG-GAN compared to state-of-the-art attack methods. Once the model is trained, MAG-GAN generates adversarial examples with minimal confusions and high attack potency [35].

To eliminate abnormal trends in actual energy usage, irregular load pattern recognition is conducted using outlier detection and clustering analysis. Although these algorithms rely on energy usage and environmental data, they yield conflicting results[9]. Incorporating these additional data points can enrich both the capacity and distinctness of the dataset, thereby enhancing the production of the model. The diagram represents a machine learning workflow that integrates GAN-based Data Augmentation with stacked machine learning models [25]. Here is an explanation of each component in the diagram:

2.2 . Training Set:

This is the original dataset used to train the model. It consists of labelled information that will be worked to create the machine learning template. The study introduces a building energy usage forecasting model for short-term predictions, employing an Artificial Neural Network (ANN) model with a Bayesian regularization algorithm. This model aims to enable real-time electricity forecasting using smart meter data, offering adaptability[10]. The self-ensembling technique, recognized as one of the effective approaches for domain adaptation in classification, involves heavily-tuned manual data augmentation. However, this augmentation method proves ineffective in mitigating the substantial domain gap[11]. The text highlights notable research and applications of the two machine learning concepts in manufacturing. However, it emphasizes that large training datasets are necessary, and tuning hyperparameters can pose challenges. Additionally, input normalization is essential for datasets with diverse parameters[12].

To diagnose the root causes of training failures, we present a credit assignment algorithm that identifies how the output of the neurons that are responsible for the failure are contributed by other neurons [39].

An efficient algorithm called FastGAN (Free Adversarial Training) designed to enhance the speed and quality of GAN training using adversarial training techniques. We evaluate our method on CIFAR10, a subset of ImageNet, and the full ImageNet datasets[40].

The main approach starts by generating lower-resolution images that capture low-frequency features through a competitive process. These images are then used to extract disentangled facial features, which are subsequently employed to produce a higher-resolution image[41].

The approachthat is proposed is assessed using theopenly available hyperspectral datasets: Indian Pines and University of Pavia. The results show that the method delivers excellent training performance even with a small amount of labelled training data [42].

We utilize this game-theoretic perspective to analyse the convergence behavior of the training process. Drawing inspiration from the fictitious play learning approach, we propose a novel training method called Fictitious GAN [43].

2.3 GAN-based Data Augmentation:

Synthetic data that resembles real data is generated by a neural network that is GAN (Generative Adversarial Networks). The data augmentation methods are used create a unified synthetic association and sub-meter profiles. They merge the on and off durations of the main appliance across diverse datasets. Nowfor further enrichment of the proposed energy disaggregation approach, the off- durations and appliance activations are combined from last 3-4 datasets. Then testing them on another dataset could yield better results[16].

Here, GANs are used to expand the original training set. This means generating additional information that is same to the original dataset. This improves the system's performance, especially when trading with small datasets.

2.4 Augmented Training Set:

The original training data is combined with the synthetic data that is generated by the GAN. This augmented dataset is then used for training.

2.5. Stacking:

Stacking is an ensemble learning technique where multiple deep learning models are workedupon the same information. Their predictions are combined to produce a final prediction.

The following models are stacked:

SGD (Stochastic Gradient Descent): A regular and effective approach for fitting linear classifiers.

SVM (Support Vector Machine): A classification technique that uses a hyperplane to separate different classes.

2.6 Meta-Estimator:

Through the stacked models, the predictions are passed to a meta-estimator. The outputs of the base model are combined in an optimal way to produce the final prediction. This model is known as the meta estimator model.

The meta-estimator essentially aggregates the strengths of all the individual models to improve overall predictive performance.

2.7. Final Prediction:

The main assumption is the output of the meta-estimator. This final output should be more accurate than that of the result of any single model in the stack could produce on its own.

Data association using GANs helps in improving the diversity of the training data, especially when the original dataset is small or imbalanced.

Stacking multiple models helps leverage the strengths of different algorithms. The meta-estimator combines their predictions to optimize the final output.

Our study reexamines MMD-GAN, which make use of the maximum mean discrepancy (MMD) as its loss utility in turn offers dual key assistance. We suggest that the current MMD loss function may hinder the understanding of main information in the facts, as it focuses on compressing the discriminator outputs for real data [46].

The generator in a standard GAN (vanilla GAN) does not impose any constraints on how the input noise is used, that may lead to a highly entangled representation of the noise. This limits the system's ability to know semantic functions that could be better captured in a disentangled manner. To address this, Info GAN is introduced, which maximizes the mutual data between the noise and the generated findings.

2.8 Variants of GAN:

I. Conditional GAN:

A conditional generative adversarial network (cGAN) provides a neural network with specific context to produce more targeted results, rather than generating random outputs. It uses conditions or information to guide the generation process. This allows for the creation of precise and desired outcomes. For instance, you can request a particular digit or an image with specific attributes. The advantage of cGANs is that they enable the model to respond appropriately in different scenarios. It explores generative possibilities for limited contexts, such as generating property designs that match a neighbourhood[19].

MedGAN employs a distinctive blend of non-adversarial losses and a novel generator architecture to accurately render the textures and intricate structures of MR images without artifacts. By incorporating phase information alongside the currently utilized magnitude data on an expanded training dataset, we can assess MedGAN's efficacy in handling complex-valued data[1]. The author utilized Long Short-Term Memory Networks, a particular type of deep neural network, to forecast various parameters such as miscellaneous electric loads, lighting loads, occupant counts, and internal heat gains in two office buildings in the United States. However, the model's physical implications are not as transparent as those of physics-based models[2]. An innovative vigrousprognosticate model for predicting complex cooling loads integrates an artificial neural network with an ensemble approach. The aim is to advance load forecasting performance through the utilization of ensemble techniques[3]. A multi-input-multi-output model based on windows is suggested for demand forecasting. Diverse optimization techniques can be devised to enhance the predictive accuracy of these learning models[4].

The approach presented in this research combines the strengths of black-box and gray-box modeling. It offers a dependable option for forecasting average temperatures on different floors of standard two-story detached houses. This method is particularly useful in scenarios where only two indoor temperature data measurements are accessible, along with basic building material properties[5]. An ensemble method employing random forest (RF) is utilized for hourly performance forecasts of GSHP systems. However, excessive iterations can lead to overfitting[6]. A Model Predictive Control (MPC) strategy is developed to effectively oversee building HVAC systems. This method is applicable and beneficial for managing large-scale buildings. Experimental validation has been conducted using a realistic simulation framework to affirm its efficacy[7]. This method merges sensor data points with encoded expert knowledge, which is pertinent to the application system but not tied to any specific deployment. It enables the enhancement of fault detection capabilities to encompass fault diagnosis, identification, and prognosis[8].

II. Progressive growing GAN:

We introduce a novel training approach for generative adversarial networks (GANs) that progressively grows the two of the generator and discriminator, thatbeginsthrough small resolutions and gradually adding layers to model finer details. This method accelerates training and improves stability, enabling the generation of high-quality images, such as CelebA images at 1024^2 resolution. The systemsuggest a technique to improve image diversity, achieving a data initiation score of 8.80 on unobserved CIFAR10. Here we also address key details of implementation to prevent detrimental contentionamong the networks and a new metric is suggested for evaluating GAN performance with respect to both quality of image and diversity. As a further benefaction, we offer an enhanced version of the CelebA dataset.

III. Style GAN:

StyleGAN builds upon the progressive GAN architecture but introduces several modifications in the generator while keeping the discriminator architecture mostly unchanged. These changes enhance the ability of the generator to create high-quality, diverse images [24]. The architectural alterations in the generator are designed to improve the control over style and features at different levels of image synthesis. Let's examine these changes individually to better understand how they impact the overall performance of StyleGAN.

The proposed method of employing multiple decomposition-ensemble techniques with error compensation, demonstrates superior performance compared to six other models. Given the significance of precise energy consumption prediction, it remains a critical concern for economic planning[13]. The suggested parallel prediction scheme can be expanded to address various time cycle prediction challenges.

This includes energy load prediction and traffic flow prediction. Additionally, an enhanced GAN architecture is proposed to better generate parallel building energy consumption data[14].

IV. Cycle GAN:

CycleGAN is a type of generative adversarial network (GAN) designed for image-to-image translation duties without needingthe paired training data. The key innovation of CycleGAN is its ability to learn transformations between two domains using two sets of unpaired images. It utilizes two generators and two discriminators, with a cycle consistency loss that enforces the idea that translating an image to the target domain which results in the original image. This method has been applied to tasks like converting photographs to paintings, changing seasons in landscapes, and other style-transfer applications.

Table 1: Advantages of the existing surveys with the proposed survey

S.No.	Advantages	Disadvantages
1.	MedGAN utilizes a unique combination of non-adversarial losses and a new generator architecture to accurately depict the textures and detailed structures of MR images without artifacts.	Integrating phase information with the existing magnitude data on a larger training dataset allows us to evaluate MedGAN's effectiveness in managing complex-valued data.
2.	The author employed Long Short-Term Memory Networks, a specific type of deep neural network, to predict diverse parameters including miscellaneous electric loads, lighting loads, occupant counts, and internal heat gains in two office buildings located in the United States.	The model's physical implications are not as evident as those presented by physics-based models.
8.	This approach combines sensor data points with encoded expert knowledge relevant to the application system but independent of any particular deployment[8].	This integration enhances fault detection capabilities to include fault diagnosis, identification, and prognosis[8].
27.	This paper concentrates on creating synthetic multi-sequence brain Magnetic Resonance (MR) images through [27]Generative Adversarial Networks (GANs).	Further research is necessary to validate our promising findings in these applications.
28.	The suggested method integrates stacked autoencoders (SAEs) with the extreme learning machine (ELM) to leverage their individual strengths[28].	It incorporates both the data and prior knowledge of periodicity to construct the[28] DNN.
29.	This paper presents an automated technique for enhancing a portrait photo, giving the subject the appearance of wearing makeup similar to another individual depicted in a reference photo.	This innovative unsupervised learning framework has potential applications in various domains beyond makeup application, including automatic aging and de-aging, as well as photorealistic object style transfer.
30.	Gradient Boosting Decision Tree (GBDT) stands as a well-known machine learning algorithm with several effective implementations like XGBoost and pGBRT. Despite numerous engineering optimizations incorporated into these implementations, their efficiency and scalability remain inadequate, particularly in scenarios where feature dimensionality is high and data size is large.	The optimization of selecting parameters a and b in Gradient-based One-Side Sampling, along with ongoing enhancements in Exclusive Feature Bundling, are crucial for improving performance, especially in handling a large number of features, whether they are sparse or dense.

We introduce the AE-OT-GAN model to leverage the strengths of both approaches: generating high-quality images while simultaneously addressing the issue of mode collapse [47].
The summary of GAN models is presented from four perspectives: first, the basic principles of GANs are explained in terms of the fundamental model and the training process; second, variations of GAN models are categorized into three main directions[48].
Results:
Analysis of Energy Consumption Model Performance Metrics:
This provides a comprehensive view of energy consumption data and the performance metrics of different predictive models used to forecast this consumption.

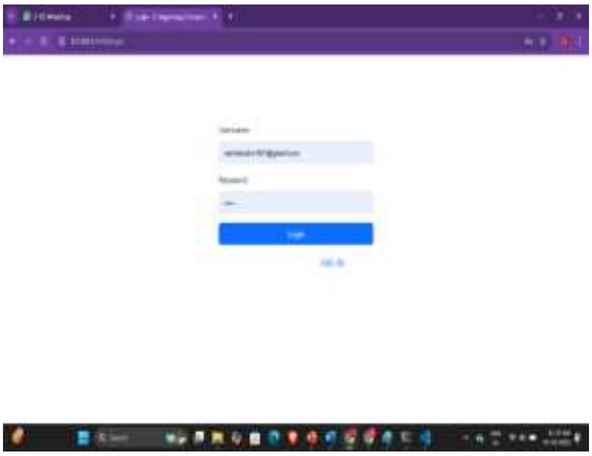

Figure 2 : Web-Interface

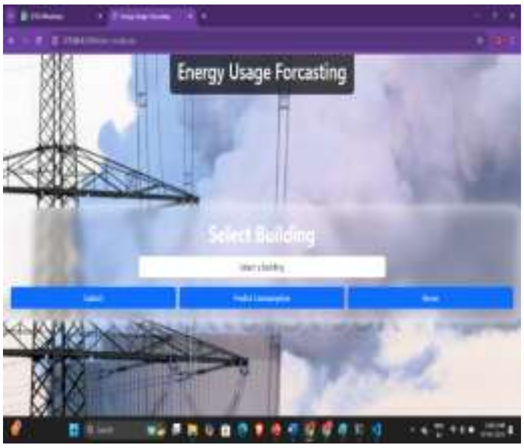

Figure 3: Web-Interface

Figure 4 :Web-Interface

Live Model Training:

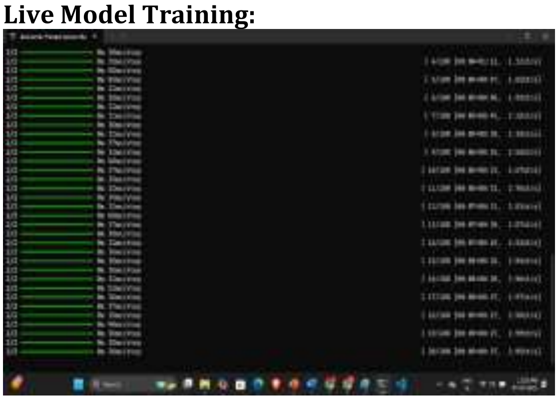

Figure 5 : Live Model Training

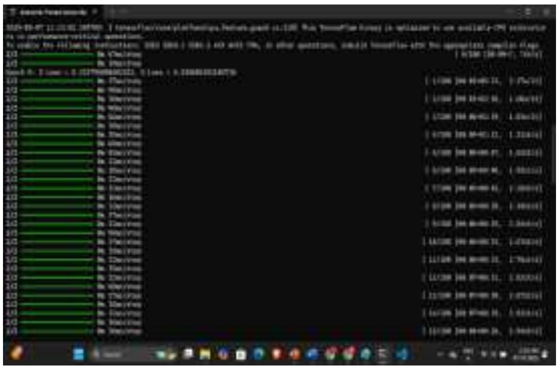

Figure 6: Live Model Training

Performance Matrix:

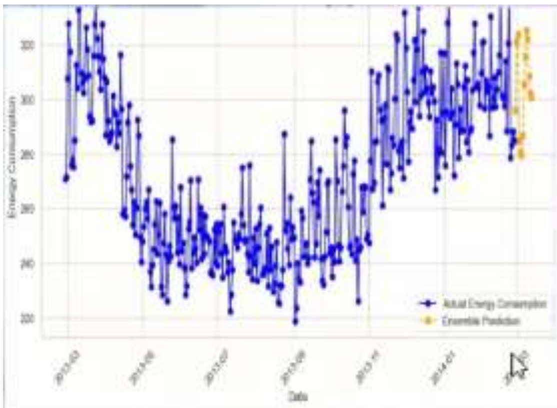

Figure 7: Performance Matrix-I

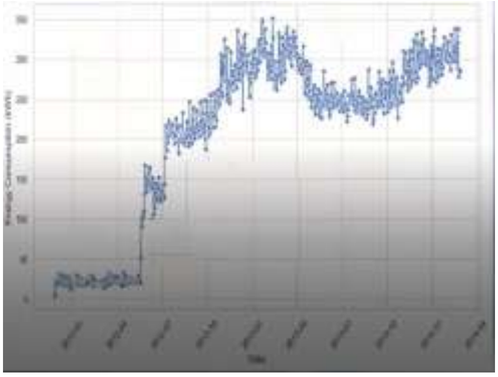

Figure 8: Performance Matrix-II

Figure 9: Performance Matrix-III

The above given figure shows energy consumption from 2013-03 to 2014-03, with values typically ranging between 220-320 kWh. There's a notable seasonal pattern with lower consumption during summer months (2013-07 to 2013-09) and higher consumption during spring and winter. The yellow points at the end represent ensemble prediction values, which appear to closely track the actual consumption.

This displays a longer period from 2012-01 to 2014-04, revealing a dramatic change in consumption patterns. The data shows:

- Very low energy usage (~20-30 kWh) until mid-2012
- A sharp transition to ~100-150 kWh in mid-2012
- Gradual increase to 200-350 kWh by early 2013
- Seasonal fluctuations similar to those in Image 1

This suggests a major change in the building's usage, occupancy, or equipment around mid-2012 (perhaps a renovation, new occupants, or installation of additional systems).

Conclusion:

In the field of the consumption of energydiagnosis, the slow pace of the graph of the variation in the electric load with time limits the ability to develop a large database for model fitting a robust model. Our research investigates a unique ensemble model intensify by Generative Adversarial Networks (GANs), incorporating two powerful performance boosters: GAN-based data expansion and stacking classifier combinations. The model combines various individual algorithms—SGD, SVC, XGBoost, LightGBM, and KNN—into strongensemble model, which is proficient on the expanded database enriched with a variety of high-quality samples generated by the GAN.

This research examines various performance models proposed by different scholars and seeks to address their limitations.

However, this work has some limitations that also indicate future directions. The study focuses on a single ensemble method, specifically stacking, and further research into other ensemble techniques is needed. Additionally, although GAN-based augmentation shows notable effects, the experiments were limited to just one GAN architecture—the vanilla version with a custom generator and discriminator design. The research should explore, test, and compare different GAN architecture variants. Moreover, the intelligent retrieval design for both the generator and discriminator could be achieved either physically or inevitably using themachine acquiring methods. Finally, the production improvements attributed to GAN were only authenticated on a single information containing correlated temperature features. More investigation is required to better understand the underlying reasons for these performance gains.Additionally, the ability of GAN to consistently improve performance across multiple datasets warrants validation.

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