

Exploring the Feasibility of Using GANs for Traffic Mitigation

Reimagining Urban Planning for Tirana's Emerging City Center

DOI: 10.37199/o41011107

Andia VLLAMASI

PhD IDAUP / POLIS University

Abstract - Tirana and other rapid growing cities are experiencing fast urbanization, which has increased traffic congestion and caused major delays and disruptions in transportation systems. In order to overcome these obstacles, network modeling and transportation indices have emerged as crucial instruments for comprehending and reducing urban traffic problems. Predicting these indices, however, becomes essential for sustainable urban planning and efficient traffic management as cities become increasingly complex.

Along with other recent advances in deep learning, the introduction of Generative Adversarial Networks (GANs) and their adaptations for spatial data analysis have provided urban planners with powerful tools to construct hyper-realistic urban layouts.

Presenting a methodology for using GANs to produce new suitable city layouts with an emphasis on traffic mitigation is the aim of this study, which also aims to explore and showcase the potential of AI, specifically GANs, in urban planning. This approach surpasses some of the traditional limitations in urban planning, particularly the ability to facilitate iterative upgrades and provide prompt performance feedback at the first stages of design.

This study investigates how the generative capabilities of GANs could speed up the design process and enable urban planners to dynamically alter layouts in response to shifting constraints and objectives. In order to create sustainable, ideal urban landscapes, this approach seeks to assess how well GANs support data-driven decision-making.

Urban planners will be able to precisely assess urban plans prior to implementation through analyzing the potential for providing traffic estimates in sequential time slots based on varying travel demands. The combination of GAN and traffic predictions will enable the generation of rapid scenarios to explore multiple design alternatives and their traffic impact.

These developments offer a revolutionary perspective to contemporary urban planning by facilitating the investigation of efficient city plans that not only reduce traffic jams but also encourage sustainable growth.

Keywords - traffic mitigation, GAN, challenges, layouts, data-driven urban planning, generative design

Introduction

According to United Nations projections, approximately 60% of the world's population, or 6 billion people, will reside in cities by 2050. This indicates that the importance of creating high-quality urban environments is growing. The physical shape of the city, together with characteristics linked to physical form, diversity, accessibility, comfort, and aesthetic quality, all have an impact on the urban environment, which serves and should meet the needs of the inhabitants in a variety of ways. Urban design is the process of organizing physical

features in urban environments, such as the shape and arrangement of buildings, the road network, public space, and green space, from the macro to the micro space, in order to create a better future environment for inhabitants. (Banerjee, 2014)

Professional urban design plans guide construction by reflecting the planner's vision for the future urban space. Numerous factors are involved since urban design solutions impact many significant facets of urban life, including transportation, pedestrian flows, social, ecological, and economic elements.

However, there are a number of issues with contemporary methods of urban spatial planning that make it difficult for them to effectively handle the complexity of urban systems. Conventional planning techniques frequently use oversimplified models that fall short in capturing the complexity of urban surroundings.

This issue presented a difficulty for the field of generative design since it required taking into account a large number of interrelated factors. The outcome of an urban project has a lasting impact on many aspects of life, and it should fulfill the demands of a rapidly growing city.

In Tirana, traffic congestion is still a major problem that calls for creative urban planning solutions. To address this issue, our objectives are:

The construction of a new, well-planned city center in Shkoza that would relieve pressure on the existing urban core and reroute traffic.

Using Generative Adversarial Networks (GANs) and other computational techniques, we aim to develop a new urban shape that incorporates a new urban core into the broader Shkoza zone makeover.

While training these models on local historical and spatial data, constraints will be applied to ensure resilient, sustainable, and functional urban development. This data-driven approach tends to encourage balanced urban expansion that minimizes traffic and enhances the city's livability by optimizing land use, transportation networks, and public spaces.

To achieve these goals, we tend to create a new framework or a methodology will step-by-step generate new urban layouts and stimulate the traffic in them, so that is can be tested before its actual execution. This will be a general framework that can be applied to different case studies.

Urban Layout Generation

Related Work

Goodfellow et al. (2014) introduced GANs, which are known for their capacity to produce synthetic data that closely mimics actual input data. They operate as two competing neural networks, a discriminator that assesses the authenticity of the data instances and a generator that generates new data instances, making it easier to create complex and realistic

data. Starting with random noise, the generator creates data that resembles real-world examples. The discriminator, in the meantime, assigns these generated outputs a probability score—closer to 1 if it thinks the data is real, and closer to 0 if it thinks it's fake—by comparing them to real samples. In a feedback loop, both networks drive one another to get better: the discriminator sharpens its capacity to distinguish between fake and real, while the generator makes its creations more persuasive.

Even though GANs are widely used in computer science, urban planning is still a relatively new field to use this technique. Despite the success of generative AI in text and image generation, cities are a complex ecosystem with human, social, economic, and topographical components. Cognitive architecture, training algorithms, complex and inaccurate data, and processing have made it challenging to combine AI with urban planning. (Wang, Lu, & Fu, 2023)

From land-use optimization to street network development and architectural design, Generative Adversarial Networks (GANs) have been used more and more in urban planning in recent years. However, GANs frequently require customization or combination with other methods, such as graph-based models, reinforcement learning, or constraint-based optimization techniques, in order to obtain optimal performance. Through these modifications, GANs are able to handle the unique complexity of many urban planning problems, guaranteeing that the designs produced are not only aesthetically pleasing but also practical, sustainable, and in line with practical limitations. The potential of GAN architectures to create intelligent, data-driven urban solutions keeps growing as they are improved and integrated with domain-specific approaches. (Weiyu Zhang, 2022)

To enhance performance and adjust to various domain tasks, numerous GAN variants have been created, each with a unique model architecture, loss functions, and strategy for resolving the model collapse problem. One of the most significant of these is the DCGAN, which incorporates the DCNN into the GAN architecture (Alec Radford, 2016). The DCGAN has been widely used and referred to as a standard and reference architecture for other variations of GANs due to its extremely high

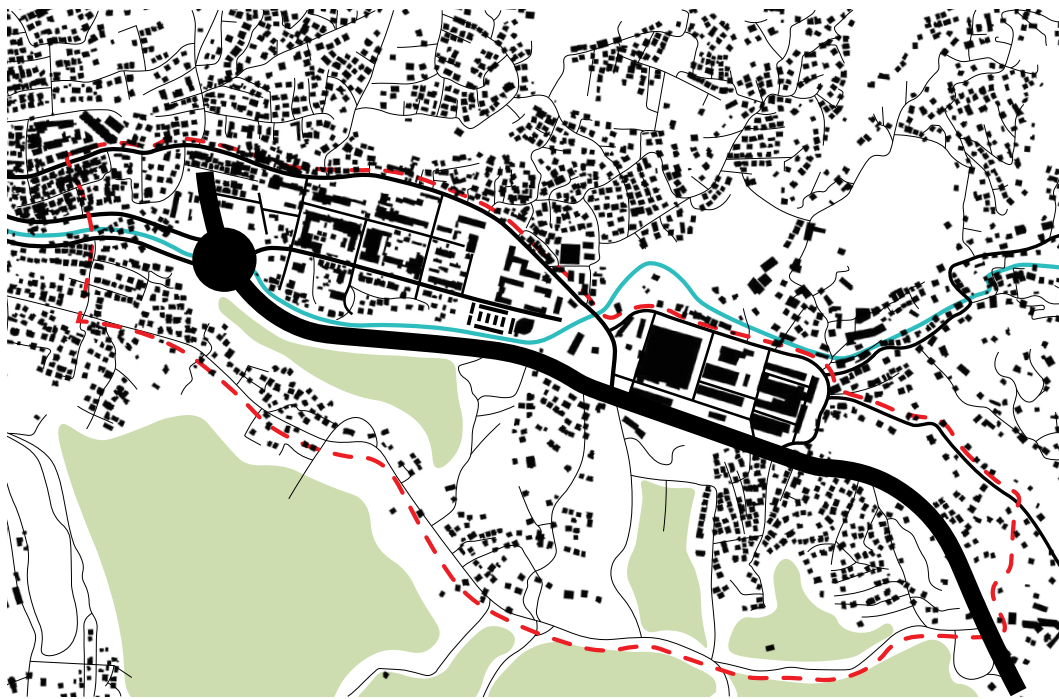


Fig. 1. Area of Study
source/ author (2024)



Fig. 2. Main Traffic Congestion Road
source/ author (2024)

Model	Application	Key Feature	Strength
DCGAN (Deep Convolutional GAN)	Image generation, feature learning, unsupervised representation learning	Uses deep convolutional layers instead of fully connected layers in both the generator and discriminator	Produces high-quality images, improves training stability, and enables meaningful latent space representations
cGAN	Street layout design	Integrates socioeconomic data	Generates realistic street networks
Rule-Based GAN	Urban layout automation	Automates dataset acquisition	Reduces manual workload in urban planning
Spatio-Temporal GAN	Traffic and mobility prediction	Handles time-series data	Improves accuracy of traffic modeling
Urban Block GAN	Urban morphology adaptation	Learns city structure patterns	Generates transferable city block designs
Urban-GAN	Participatory urban design	Democratizes urban planning	Enables citizen co-creation of urban spaces
UrbanGenoGAN	Large-scale urban planning	Integrates GA, GAN, and GIS	Optimizes urban plans under multiple constraints
MetroGAN	City expansion modeling	Uses hierarchical learning and geographical loss	Enhances urban morphology prediction
StackGAN	Produces realistic, high-resolution graphics from text-based descriptions.	Structure is created by two GANs, ADGAN and UrbanGAN Involves fine-tuning	Mimics the logical morphological control of human architects and learns historical layout traits.

Tab. 1. GAN architectural combinations, application, key features and strengths
source/ author (2024)

performance in image classification and other generation tasks with significantly improved training stability (Hong, 2019). The street patterns, architectural plan layout, street views, and urbanization patterns (Adrian Albert, 2018) are just a few of the urban plans and design schemes that have been produced by several studies using GANs, and more especially DCGANs. A few of them had outstanding outcomes. The majority of these research, which primarily targeted planners and designers, employed GANs to create

2D plans or images in a manner similar to that of natural picture creation in computer science. Many of them, however, failed to adequately explain how GANs benefit specialists who are capable of completing the identical design assignment with a far higher degree of complexity and quality. (Boim, 2022) illustrated the application of a conditional GAN known as Pix2Pix for predicting and modeling urban forms, integrating AI into the city design. Moreover, he constructed a Pix2Pix CGAN model for image-to-image translation. This

also serves to further highlight the importance of AI in visualization of urban changes.

CGAN has also contributed in street layout design, by integrating socioeconomic and natural contains such as elevation, population density and land use. The input data is first encoded by this model using an autoencoder that creates a feature map by combining socioeconomic and natural restrictions. After that, a conditional GAN is trained on actual street networks to produce layouts that closely resemble real-world urban street configurations both structurally and aesthetically. The produced image-based street layouts are transformed into vectorized street graphs for implementation using an extraction program. (Lehao Yang, 2023)

One interesting modification of GAN is a framework called Stack-GAN that uses a stacked approach. It consists of two GANs, the first of which uses the data as input to capture fundamental features, and the second of which uses the output to refine the data. This demonstrates the concept of fine-tuning that has been employed lately to improve a machine learning model's performance on a particular task. (Zhong, 2024) These findings underscore the necessity of a hybrid approach in which GANs complement conventional planning tools to produce data-driven but realistic urban solutions.

The following table lists different GAN architectural combinations, emphasizing the variations in their application, key features and strength.

In one form or another these works demonstrate the expanding use of AI in urban planning and reaffirm the necessity of integrating GANs with real-world restrictions, optimization methods, and expert knowledge. Their results provide credence to the approach put forth in this study, which uses GANs to create a new, sustainable city core in Shkoza that will reduce traffic and encourage effective urban expansion.

Potential Solution for Generation of New Urban Center

To illustrate how the suggested framework will function, this study used a Uzina hypothetical design project as a pilot case study. Using GAN to generate urban design to improve connections and bring back the neighborhood is one of the major changes I tend to apply for Uzina. Based on some site analysis we decided to make some changes for the area.

First, instead of depending on just one access point, since Tirana's Big Ring has now become one of the more important connection roads in Tirana, we suggest setting up several connections to it. By minimizing congestion on the major arterial roads and facilitating more seamless mobility, this strategy will aid in the more efficient distribution of traffic flow. Second, the regeneration of the old Uzina and its potential conversion into a dynamic urban area that might serve as Tirana's second city center are at the core of this change.

We may rethink this traditionally industrial region as a mixed-use zone that integrates public, commercial, and cultural amenities, so we tend to increase its social and economic effect, rather than allowing it to remain unused. (Figure 3)

Other cities have successfully investigated this kind of AI-driven urban renewal. For example, Urban-GAN framework (Quan S. J., 2022) has demonstrated how AI can integrate past urban morphologies into contemporary designs, allowing cities to maintain their unique identity while meeting contemporary demands. Similar to this, WeiYu Zhang et al's (Zhang, 2022) MetroGAN has been used to model changes in urban morphology while making sure new construction complies with connectivity and infrastructure standards.

A similar example is the redevelopment of Milan's industrial district, where AI-aided urban modeling assisted in converting vanished industry areas into vibrant, multipurpose areas that enhanced accessibility and strengthened local identity. (Bergaglio, 2019). We can also mention a lot of other revitalized industrial areas like King's Cross (London, UK), Emscher Landscape Park (Ruhr Region, Germany), Nordhavn (Copenhagen, Denmark), making this a great idea for the developments of

this areas. (Bartsch, 2006)

We can create a more connected, useful, and lively urban environment by implementing these AI-driven urban planning approaches will make this transformation easier. This will optimize traffic patterns and turn the area from a bypassed industrial relic into a central destination. (Zahra Jaffari, 2020)

Through the use of these AI-powered urban planning techniques, Uzina's transformation may be historically informed, data-driven, and participatory. This strategy guarantees that traffic patterns are optimized, traditional urban morphologies are preserved, and the region is transformed from an overlooked industrial remnant into a major destination.

Policymakers can select the most sustainable, useful, and community-driven form of Uzina's second city core by using GAN models, which have been utilized in other regeneration initiatives to create numerous urban futures.

Methodology

Data Sources

Urban planning has benefited greatly from the use of Generative Adversarial Networks (GANs), which enable the creation of data-driven and realistic urban plans. Their capacity to identify patterns in preexisting city layouts and develop new shapes that resemble actual structures is what makes them strong.

One significant drawback of GANs is how heavily they rely on massive amounts of data for training. This is the main obstacles of using GAN-based urban planning especially in developing towns like Tirana where we have limited data available.

Tirana, like many cities in countries with limited resources, struggles with data scarcity in contrast to major metropolitan regions that have substantial GIS datasets, satellite imagery archives, and structured urban planning records. To train this algorithm, urban form database is needed that must consist of satellite images of the urban area, land cover, spatial layers, longitude and latitude data points and computed landscape metrics. GAN models need enormous volumes of training data to produce realistic urban layouts, but with the increasing availability of the data we tend to make this real. We must first will create a framework that permits gradual AI integration into the planning process rather than immediately producing a fully functional AI-driven city design.

HybridGAN Framework

To ensure the achievement of all our goals, we have created a framework called HybridGan, name that reflects its hybrid nature, which involves the integration of different tools and methods into a unified structure. The framework workflow is also demonstrated at Figure 4.

After collecting and processing the data, an essential step for training the algorithm, the shortcomings of which were discussed above, the most important phase of this framework follows. The main part of this

framework is the generation of the city new urban areas layout. In order to generate city layouts where we will apply constraints relevant to planning goals, we should involve a detailed pipeline.

Some of the constraints that we will need to apply:

- Regulations governing: minimum and maximum amounts of green space or the width of roads
- Land use ratios: residential to commercial regions
- Sustainability Goals: the improvement of bike

lanes and walkability, streamline traffic, and congestion reduction

- Accessibility: to transit hubs and key points of interest.

- Custom constraints: the intended connectivity between communities and the location of a new city center.

Despite the constraints, numerous researches have experimented with various GAN data labeling setting (DLS) approaches (Wei Li, 2023) to address the challenge of managing the GAN label process to enable the fulfillment of overriding design criteria.

DLS is a crucial GAN data processing procedure that might affect how individuals work with DL models. An improved DLS technique is required to incorporate the physical data that is currently available and the urban planners' hypothesis label as GAN input in order to improve the architect's decision-making in GAN applications.

After generating the new urban area, we continue with an essential step, that of traffic simulation, in order to analyze and evaluate the functionality of this new area.

- Advantages of combining traffic forecasting with GAN:

- Rapid Scenario Generation: Investigate several design options and their effects on traffic as soon as possible.

- Traffic Optimization: Put your attention on creating layouts that give priority to effective transit systems.

- Data-driven insights: assessing design prior to implementation by utilizing predictive models and historical data.

- Iterative Planning: improve urban layouts by adjusting designs in response to traffic performance.

Tools and Libraries

Data collection and Processing: QGIS, ArcGIS for spatial analysis, OpenStreetMap for road network data

GAN: TensorFlow or PyTorch, frameworks like Pix2Pix/CycleGan for conditional tasks

Simulation tools: UrbanSim for development modeling, SUMO for traffic flow analysis

Stakeholder Inclusion

Simul There is an important step after finding and testing the right GAN architecture for our purpose.

This step is including public opinions in the design process. Professional designers and urban planners take the control of design generation with the assumption that they can represent the public, thereby completely ignoring public participation.

We should address this problem and finding a way to use the increasing power of AI and allow the public without design expertise to generate their own physical schemes.

Through the integration of interactive digital tools (such as touchscreens, mobile apps, and web-based applications), the system enables users to engage with design concepts, transform components, and improve urban forms prior to their final approval.

When compared to conventional urban planning, where professionals specify city layouts, we want to encourage collaborative design creation, in which the general public actively shapes the cityscape rather than merely offering input. AI is included into the design creation process to automatically learn and represent communal design preferences from examples chosen by citizens.

Whenever the AI-generated design fails to satisfy the public, the system continues to modify and improve the urban form. A database containing the developed design schemes gradually accumulates

user-driven design knowledge.

The inclusion of public has a lot of limitation, since the system might need priority filtering techniques to conclude disagreements between various community demands because urban planning involves a wide range of stakeholders.

Although the approach gives residents more authority, professionals are needed to handle limitations including zoning regulations, environmental concerns, and infrastructure requirements. Policy-driven constraints could be incorporated into future iterations to guarantee that created designs comply with regulatory frameworks.

Conclusions

This study investigates how Generative Adversarial Networks (GANs) might revolutionize urban planning. In addition to simulating new urban forms that are morphologically sound and spatially cohesive, the suggested method focuses on employing GANs to address urgent issues including traffic congestion, fractured connectivity, and the need for sustainable development in increasingly urbanizing areas. But difficulties still exist, particularly in settings with limited data, which are common in many developing cities. In order to set the groundwork for upcoming AI-driven planning projects, this study recommends a staged framework that begins with data preprocessing, progresses to hybrid GAN training, participative simulation and traffic simulation.

In the end, Uzina's transformation into a thriving, interconnected, and sustainable city core makes a strong argument for integrating the creativity of humans with machine intelligence, putting GANs at the epicenter of next-generation urban planning.

References

Adrian Albert, E. S. (2018). *Modeling Urbanization Patterns with Generative Adversarial Networks*. arXiv preprint arXiv:1801.02710.

Alec Radford, L. M. (2016). *Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks*. International Conference on Learning Representations. ICLR.

Banerjee, T. (2014). *Urban Design*. In A. C. Michalos (Ed.), *Encyclopedia of Quality of Life and Well-Being Research* (pp. 6912–6917). Dordrecht: Springer.

Bartsch, E. C. (2006). *Industrial Site Reuse and Urban Redevelopment—An Overview*. *Cityscape: A Journal of Policy Development and Research*, Vol. 2, No. 3. U.S. Department of Housing and Urban Development (HUD).

Bergaglio, M. (2019). *Inhabit Utopia: A new outcome for large regenerated industrial areas in Milan*. In *Scrivere la terra, abitare l'utopia: comunità e migrazioni* (pp. 14–22). Italy: ISPI – Istituto di Studi Politici Internazionali.

Boim, N. S. (2022). *Architectural Form Explorations through Generative Adversarial Networks - Predicting the potentials of StyleGAN*. Retrieved from Research Gate.

Goodfellow. (2014). *Generative Adversarial Networks*. *Advances in Neural Information Processing Systems (NeurIPS)*.

Hong, S. Y. (2019). *How Generative Adversarial Networks and Their Variants Work: An Overview*. *ACM Computing Surveys*. CSUR.

Lehao Yang, L. L. (2023). *Street Layout Design via Conditional Adversarial Learning*. *Computational Urban Science Journal*, 4(1), 20-35.

Lingcao Huang, T. C. (2022). *Accuracy, Efficiency, and Transferability of a Deep Learning Model for Mapping Retrogressive Thaw Slumps across the Canadian Arctic*. *Remote Sensing*, MDPI.

Quan, S. J. (2022). *Urban-GAN: An artificial intelligence-aided computation system for plural urban design*. *Environment and Planning B: Urban Analytics and City Science*.

Quan, S. J. (2022). *Urban-GAN: An artificial intelligence-aided computation system for plural urban design*. *Environment and Planning B: Urban Analytics and City Science*, Volume 49, Issue 9.

Wei Li, C. G. (2023). *DLS-GAN: Generative Adversarial Nets for Defect Location Sensitive Data Augmentation*. *IEEE Transactions on Automation Science and Engineering*, 1-17.

Weiyu Zhang, Y. M. (2022). *MetroGAN: Simulating urban morphology with generative adversarial network*. *28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining* (pp. 2482–2492). Washington, DC: Association for Computing Machinery (ACM).

Zahra Jaffari, U. A. (2020). *Adaptive Reuse of Industrial Spaces in Urban Revitalization*. *OSF Preprints*.

Zhang, W. M. (2022). *MetroGAN: Simulating Urban Morphology with Generative Adversarial Network*. *28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. Association for Computing Machinery.

Zhang, Y. L. (n.d.). *Curb-GAN: Conditional urban traffic estimation through spatio-temporal generative adversarial networks*. Worcester Polytechnic Institute, University of Iowa, & Lenovo Group Limited.

Zhong, X. L. (2024). *A framework for fine-tuning urban GANs using design decision data generated by architects through GANs applications*. CAADRIA, Singapor.