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A Brief Introduction to Deep Generative Models for Civil Structural Health Monitoring

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Abstract. The use of Deep Generative Models (DGMs) such as *Variational Autoencoders*, *Autoregressive Models*, *Flow-based Models*, *Energy-based Models*, *Generative Adversarial Networks*, and *Diffusion Models* has been very advantageous in various disciplines and one of the most trending research activities in the Artificial Intelligence field in recent years. On the other hand, the research and development endeavors in the civil structural health monitoring (SHM) area have also been very progressive owing to the increasing use of Machine Learning techniques. As such, some of the DGMs have also been used in the civil SHM field lately. This short study aims to assist researchers in the civil SHM field in understanding the fundamentals of DGMs and, consequently, to help initiate their use for current and possible future applications. On this basis, this paper briefly introduces the concept and mechanism of each DGM. Some of the DGMs have not been utilized or exploited fully for SHM to the best knowledge of the authors during the preparation of this manuscript in December 2022. Accordingly, some of the studies presented in the civil SHM field that use the members of DGMs are mentioned.

Keywords: *Deep Generative Models, Structural Health Monitoring*

Deep Generative Models

Structural Health Monitoring (SHM) typically consists of sensing and instrumentation, data collection, preprocessing, analysis, and evaluation phases, followed by decision-making. Thus, it includes various types of data-driven solutions. During the last few decades, the research and development in the civil SHM field have been very progressive due to the increasing use of Machine Learning (ML) to address the challenging problems faced in the field (Catbas et al. 2022). ML-based techniques have been a research trend for the last few decades in many SHM applications. Deep Generative Models, in short DGMs, are generative models with many hidden neural networks that have been highly favored in recent years across various disciplines. They are a powerful way of learning hidden data representations in data distributions and generating new data points with some variations by leveraging the flexibility of deep neural networks. Rather than creating a decision boundary in the data distribution for classification purposes (discriminative approach), the generative approach aims to learn how the data distributions are shaped. The deep neural networks are used in DGMs to parametrize the generative models, increasing the model's capacity. When the DGMs are trained successfully, they can generate a new data point similar to the data points from the unknown distribution. DGMs generally consist of six members (Bond-Taylor et al. 2022; Jakub M. Tomczak 2022; Ruthotto and Haber 2021): Autoregressive Models (AMs), Variational Autoencoders (VAEs), Flow-based models (FBMs), Energy-based Models (EBMs), Generative Adversarial Networks (GANs), and lastly Diffusion Models (DMs). The general concepts of the DGMs are briefly explained below without getting into mathematics. **Figure 1** illustrates the summary of the mechanisms of Deep Generative Models (Weng 2021).

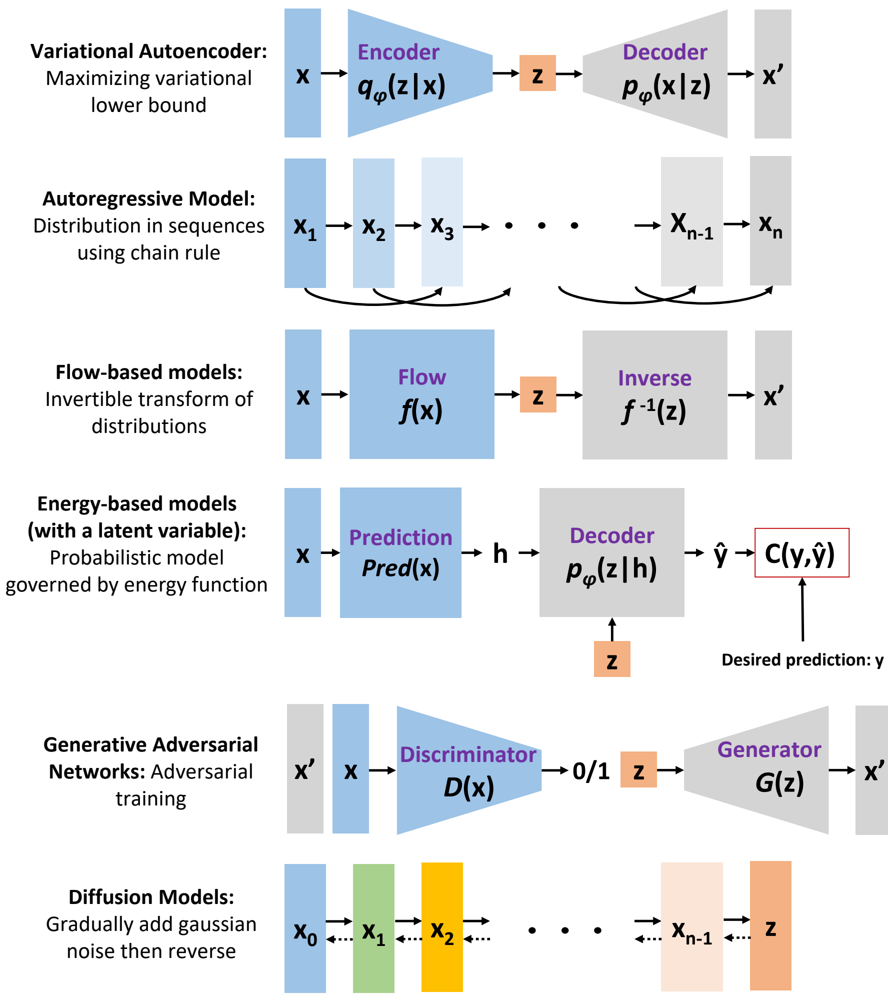


Figure 1. Overview of the Deep Generative Models, where x and x' is, respectively, original and synthetic data, z is the latent variable; y and $\hat{y}$ the desired prediction and resulting prediction; f is the invertible transformation function; $q_\varphi(z|x)$ and $p_\varphi(x|z)$ are the probabilistic encoder and decoder; $D(x)$ and $G(x)$ are the discriminator and generator. While likelihood-based models such as VAEs, AMs, FBMs, EBMs, and DMs can be trained stably, training implicit models like GANs can be unstable. In VAE, only the lower bound is provided, and the likelihood function cannot be precisely computed, which is also true for EBMs requiring calculating the partition function. AMs suffer from the sampling process, which makes the inference extremely slow due to the autoregressive manner of generating new data points; however, they are the most efficient likelihood models. EBMs and DMs require to run Monte Carlo for inference, slowing down the generation. Nevertheless, DMs are currently state-of-the-art DGM, demonstrating better generative performance than even GANs (Dhariwal and Nichol 2021a).

Variational Autoencoders (VAEs): VAEs were first introduced in (Kingma and Welling 2013) using a similar architecture as autoencoders: an encoder (sometimes referred to as recognition model) to obtain the latent space and a decoder (sometimes referred to as generative model) to re-produce the data from latent space. Therefore, VAEs are primarily associated with autoencoders, but their working principles, such as objective functions, differ. The goal of VAEs is to define an observation using a probabilistic approach in a continuous latent representation (compressed information) rather than having an encoder which gives a single value to define each latent state attribute (autoencoders). Basically, the VAEs are comprised of a probabilistic encoder and decoder with a parametrized likelihood function (maximization of variational lower bound) for variational data generation in an unsupervised manner. Leveraging this probabilistic approach integrated with an autoencoder helps VAEs to achieve outstanding data generation performances in many studies (Kingma & Welling, 2019; Mayank Mittal & Harkirat Singh Behl, 2018), which are often compared with GANs in terms of their generation performances. Several studies were presented employing VAEs in civil SHM for various purposes, such as anomaly detection (Zhou et al. 2022), damage identification (Ma et al. 2020; Pollastro et al. 2022) or optimal sensor placement (Sajedi and Liang 2022) (**Figure 2**) addressing data scarcity challenge in SHM domain in one way or another.

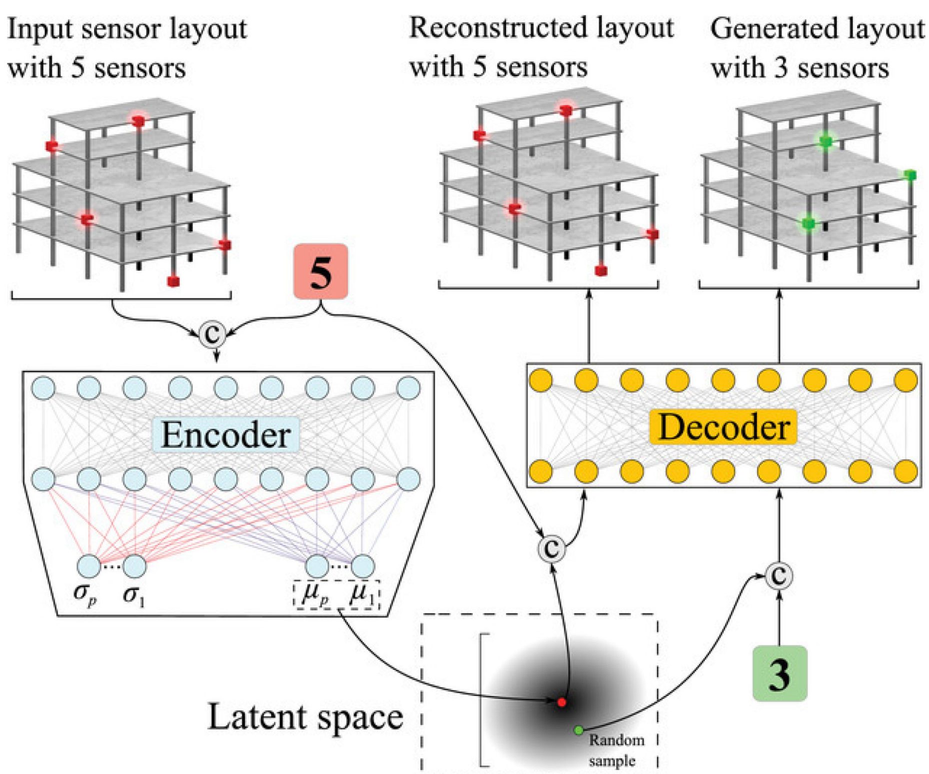


Figure 2. Generating sensor placement layouts with a particular number of sensors using a conditional variational autoencoder, where the introduced methodology is tested on a nine-story reinforced concrete moment frame (Sajedi and Liang 2022).

Autoregressive Models (AMs): AMs implicitly determine a distribution over sequences by using the chain rule for conditional probability. In this sequence, each step in the distribution is predicted based on the previous steps. Basically, AMs take the previous data in a sequence to predict a future value in that sequence. Thus, AMs are generally a better fit for time series with an intrinsic sequence of time steps, which is where they truly excel. One of the best-known models is WaveNet for audio generation (Oord et al. 2016). AMs are also used for images using sequential models for the pixels, such as the PixelCNN model [30] but are not state-of-the-art in image generation. Among other DGMs, it is essential to note that AMs are sequential but are still feedforward. Additionally, while they are generative, they still use a supervised approach. These facts make AMs faster, more stable in training (but slow in inference and have poor scaling properties), and more straightforward and intuitive than the other DGMs. In civil SHM, AMs have been quite popular among researchers for years; however, they were mainly used for feature extraction, pattern recognition, anomaly detection and future data estimation (**Figure 3**) (Entezami et al. 2021; Gul and Necati Catbas 2009; Psathas et al. 2022).

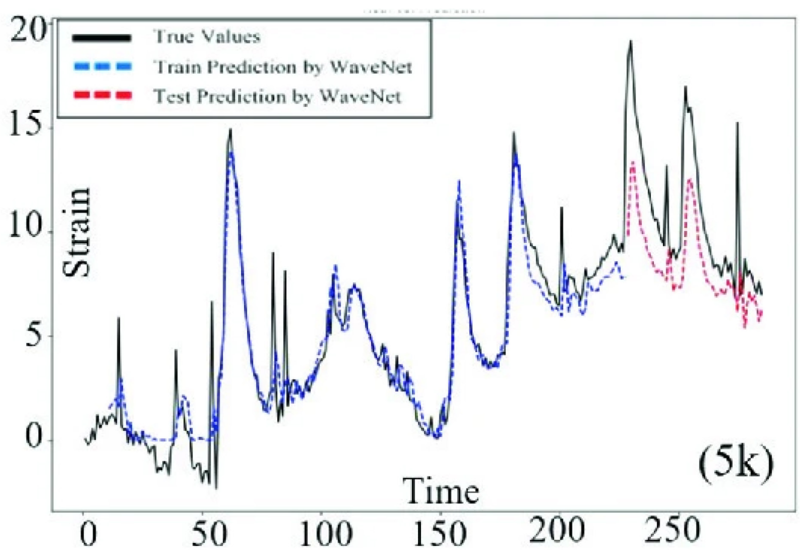


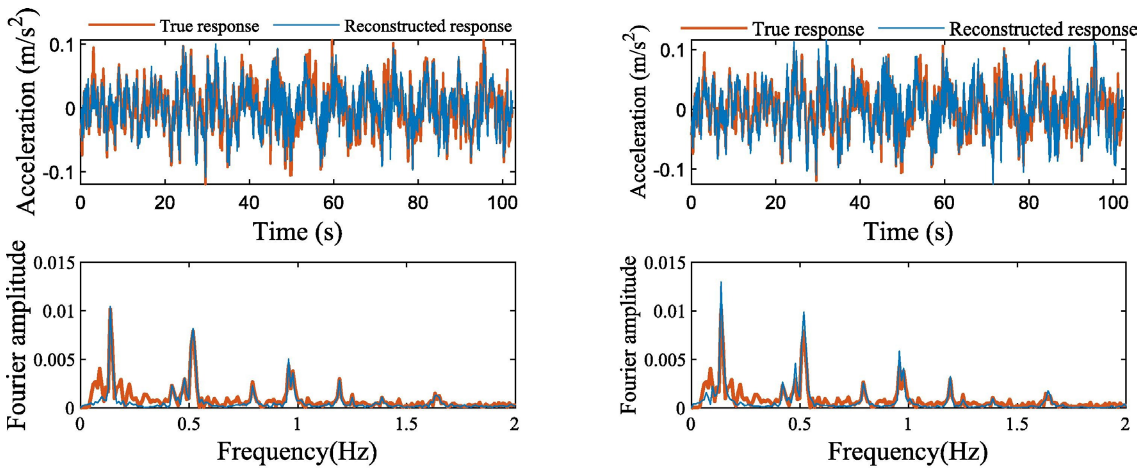
Figure 3. The ground truth strain response values collected from a bridge structure (black), the estimated strain train data (blue), and the estimated strain test data (red) using WaveNet (Psathas et al. 2022).

Flow-based Models (FBMs): VAEs and GANs do not explicitly learn the probability density of real data and are intractable. FBMs (Danilo Jimenez Rezende and Shakir Mohamed 2015) are a type of DGM that tackles this challenge by modelling a probability distribution using normalizing flows, a statistical tool for density estimation. In other words, FBMs learn the probability density explicitly, and they are tractable. FBMs being tractable also makes the objective of the training simply the negative log-likelihood. Normalizing flows assist FBMs in modelling for a better distribution approximation leveraging the change-of-variable theorem of probabilities for transforming a distribution into a complex one by applying a sequence of invertible transformation functions. The variables are repeatedly substituted for a new one based on the change-of-variable theorem to obtain a probability distribution of the end target variable.

Basically, FBMs are constructed by a sequence of invertible transformations with the help of normalizing flows. Some notable FBMs are available in these references: (Kingma and Dhariwal 2018; Laurent Dinh et al. 2015). In addition, more recently, the normalizing flows were incorporated into a Diffusion Model (Qinsheng Zhang and Yongxin Chen 2021). To the best of the authors' knowledge, the use of FBMs for SHM has not been observed during the preparation of this manuscript.

Energy-based Models (EBMs): EBMs appeared in the ML field in the early 1980s (Ackley et al. 1985; Hopfield 1982), and since then, it has been improved and extended (LeCun et al. 2006). EBMs are a probabilistic model controlled by an energy function that defines the probability of a particular state. Essentially, they capture data dependencies by applying a probability scalar energy (a measure of compatibility) to each configuration of the variables. Inference includes setting the value of observed variables to 1 and then finding the values of the rest of the variables, which minimizes the energy. Learning can also be accomplished by obtaining an energy function that correlates low energies with correct values of the rest of the variables and higher energies with incorrect values. EBMs use a unified framework combining all the probabilistic and non-probabilistic approaches for learning, especially for training graphical and structured models. The challenge of estimating normalization constant in probabilistic models does not exist in EBMs, which allows for more flexibility in the design of the learning process. However, EBMs suffer from modeling high-dimensional data. Although EBMs have been a research field for several decades, including some recent studies (Junbo Zhao et al. 2017; Shuangfei Zhai et al. 2016; Yilun Du and Igor Mordatch 2019), no studies are observed using EBMs in the civil SHM field, again to the best knowledge of the authors at this time.

Generative Adversarial Networks (GANs): When GAN was first released in 2014 (Goodfellow et al. 2014), it received significant attention due to its novel approach (adversarial training concept – minimax game) and cutting-edge performance in image generation. GAN contains two networks: a generative network and a discriminator network. Essentially, the generator learns to generate similar data samples to the real dataset based on the discriminator's output while the discriminator is also learning about the real data domain. In other words, both networks attempt to overcome each other in a minimax game; while the generator tries to fool the discriminator with the generated images, the discriminator tries to predict the synthetic and real images. Followed by its release, many researchers focused on improving the training of GAN due to its well-known unstable and no-convergence training process and mode collapse (less diversity in generated outputs) (Arjovsky et al. 2017; Goodfellow 2016; Gulrajani et al. 2017; Salimans et al. 2016). Moreover, there are many notable works using GANs, such as CycleGAN (Zhu et al. 2017), StyleGAN (Karras et al. 2018), and ESRGAN (Wang et al. 2018). Using GANs (original GAN and variants) for civil SHM applications is a popular research activity, and they were found beneficial for several challenges in SHM (**Figure 4**) (Fan et al. 2023; Jiang et al. 2022; Lei et al. 2021; Luleci et al. 2021a; b, 2022a; b). GANs were considered state-of-the-art generative models by many in terms of the quality of their generative performances until the recent rise of Diffusion Models (DMs).



(a) (b)

Figure 4. (a) The original and reconstructed acceleration responses in the time and frequency domain using self-attention mechanism enhanced generative adversarial network; (b) The original and reconstructed acceleration responses in time and frequency domain using segment-based generative adversarial networks (Fan et al. 2023).

Diffusion Models (DMs): DMs are inspired by non-equilibrium thermodynamics (Sohl-Dickstein et al. 2015), aiming to develop a learning approach that achieves analytical flexibility and tractability. The essential concept of DM is to successively add random noise to the data (image) through a Markov chain sequence to eventually obtain an isotropic Gaussian noise. Then, learn to reverse the forward diffusion process via backward propagation to reconstruct (or denoise) the desired data from the Gaussian noise. Some of the major differences of DMs between and the other DGMs are being able to generate highly realistic images and yield more diversity even better than GANs, having stable training procedures, and being able to be conditioned on a wide variety of inputs (Dhariwal and Nichol 2021b; Ho et al. 2020; Song and Ermon 2019). One other unique property of DMs is that the latent space has the same dimensionality as the original data, which benefits DMs in terms of less computation. More recently, DMs have also shown remarkable success in image and video generation, such as Imagen (Saharia et al. 2022) and Imagen Video (Ho et al. 2022) from Google, Dall-E 2 (Ramesh et al. 2022) from OpenAI and Make-A-Video (Singer et al. 2022) from Meta. Since DMs are a new research area in the Artificial Intelligence field, no study seems to have been in the literature using Diffusion Models in the SHM domain.

Discussion, Summary, and Conclusion

The research and development in the civil SHM domain have been very progressive for the last few decades due to the increasing use of ML to tackle the challenging problems faced in the field (Avci et al. 2021; Azimi et al. 2020; Bao and Li 2021). On the other hand, using Deep Generative Models (DGMs) has also been a trend across many disciplines lately, demonstrating very efficient solutions for particular applications. Civil SHM is one of these disciplines that researchers have just begun exploring to use some members of DGMs towards SHM applications. While no studies exist using FBMs, EBMs, and DMs based on our recent review of the literature (as of December 2022), quite a few works are available using GANs in the civil SHM domain. On the other hand, AMs are primarily used for feature extraction, pattern recognition, anomaly detection, future data estimation and similar applications. Lastly, several studies use VAEs in civil SHM for various purposes, such as anomaly detection, damage identification or optimal sensor placement.

It is important to note that data scarcity is a significant challenge in civil SHM due to data collection from civil structures being challenging. While data collection from every civil structure is not economically feasible, a large portion of the structures is worth monitoring due to the growing concern for the better management, operation and safety of civil structures. Even when a few of them are monitored, SHM system-based errors (sensor or transmission errors) are very typical, resulting in sensorial data loss. The fact that SHM applications such as damage diagnosis and prognosis rely on data-driven solutions makes the challenge of data scarcity even more significant. Therefore, employing Deep Generative Models for SHM applications is critical, considering their record-breaking data generation performances as demonstrated in the literature. As such, they can be used to tackle several challenges faced in SHM (Luleci et al. 2022b), such as:

- *Lost data reconstruction* to recover the lost or missing data due to SHM sensorial or transmission errors,
- *Data augmentation* to improve the low performance in damage diagnosis/prognosis applications due to class imbalance of the training dataset,
- *Data domain translation* to enable access to the paired data points for the latter damage diagnosis/prognosis applications.
- *Anomaly and novelty detection* to identify anomalies in structural behavior measurements, which could indicate potential issues with the structure.

In addition, DGMs could be trained on structural response datasets to different loading conditions, such as wind or earthquakes, to *generate structural behavior simulations*. These models could then be used to generate simulations of how a structure is likely to respond to different types of loading, allowing engineers to understand the behavior of the structure better and identify potential areas of weakness.

Lastly, by training DGMs on large datasets of structural failure modes, it may be possible to develop algorithms that predict the likelihood of failure in a given structure. This could help engineers prioritize repairs and maintenance and take preventative measures to avoid catastrophic failures.

It can be argued that there is a big room for research and development using DGMs for data generative-based applications in the civil SHM field. Although this is one clear need, another issue is to introduce these concepts to relevant studies on civil structures for the initiation of the research and further development of these novel concepts for the SHM domain.

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