We can rewrite the conditional into $p(\mathbf{x}|\mathbf{z}) = \frac{p(\mathbf{x},\mathbf{z})}{p(\mathbf{z})}$ such that we get for the joint probability density:

$$p_{\hat{\theta}}(\mathbf{x},\mathbf{z}) = p_{\hat{\theta}}(\mathbf{x}|\mathbf{z})p_{\hat{\theta}}(\mathbf{z}) \tag{1}$$

Let G=(V,E) be a Bayesian Belief Network.
Furthermore, for every node $\mathbf{y} \in$ V its parents are random variables that $\mathbf{y}$ is conditioned on. Let $\pi(\mathbf{y})$ be the set of parents of $\mathbf{y}$. Then we have that:

$$p(\mathbf{y}_1, ..., \mathbf{y}_l) = \prod_{i=1}^{l} p(\mathbf{y}_i|\pi(\mathbf{y}_i)) \tag{2}$$

Every directed edge in E has a potential that is defined by a probability. If $\mathbf{y}_j \in \pi(\mathbf{y})$ the probability to reach $\mathbf{y}$ from $\mathbf{y}_j$ is defined by $p(\mathbf{y}|\mathbf{y}_j)$. Then the graph of a generator looks like that:

$$\xrightarrow{p(\mathbf{z})} \mathbf{z} \xrightarrow{p(\mathbf{x}|\mathbf{z})} \mathbf{x}$$