# DIGITAL TWIN

# PROJECT

# REPORT

## Abstract

The rapid adoption of autonomous vehicles (AVs), particularly electric AVs, is transforming urban energy systems. This shift, while promising in terms of safety and efficiency, presents challenges for electricity demand and renewable energy integration. This project develops a system dynamics model using Vensim to analyse the interplay between AV adoption, electricity demand, and renewable energy capacity. The model explores how factors such as AV market growth, charging infrastructure, policy support, and energy efficiency influence the sustainability of this transition. Key objectives include estimating electricity demand from AVs and evaluating whether renewable energy capacity can meet this growing demand under different policy and technological scenarios.


## Introduction

Digital Twin (DT) technology enables the creation of dynamic virtual models that mirror real-world systems. These models support analysis, monitoring, and simulation-based decision-making. In the context of urban transportation and energy systems, DTs allow researchers and policymakers to anticipate the impacts of new technologies such as autonomous vehicles (AVs).

As AVs—especially electric AVs—become more prevalent, cities face a dual challenge: rising electricity demand and the need to transition to renewable energy sources. This project focuses on building a Vensim-based digital twin to explore whether the renewable energy infrastructure can sustainably support AV growth. The model simulates policy interventions, technology advancements, and energy efficiency improvements to provide insights into energy system resilience.

## Problem Statement and Objectives

The adoption of electric autonomous vehicles is expected to drastically alter urban electricity consumption patterns. While they reduce fossil fuel dependence, the corresponding surge in electricity demand may strain existing infrastructure and delay renewable energy goals.

Objectives:

- To estimate the increase in electricity demand due to AV adoption.
- To model renewable energy capacity growth and its ability to meet new demand.
- To identify key levers such as policy incentives, charging infrastructure, and AV efficiency.
- To evaluate long-term sustainability scenarios using Vensim.

# Vensim Model Description

The system dynamics model consists of two main modules:

- AV Electricity Demand
- Renewable Energy Capacity

Key Model Components:

| Stock Name | Equation | Units |
|---|---|---|
| **No of AV's** | `INTEG (AV adoption rate - AV retirement rate, 50000)` | Vehicles |
| **Installed renewable capacity** | `INTEG (Renewable capacity addition rate - Renewable capacity decommission rate, 1e+07)` | MWh |
| **Simulation time** | `INTEG (time increment, 0)` | Year |
| **Total Electricity demand** | `INTEG (Electricity Demand from AV, 0)` | MWh |

| Flow Name | Equation | Units |
|---|---|---|
| **AV adoption rate** | `AV market share * Total Vehicle market share * (1 - market resistance)` | Vehicles/Year |
| **AV retirement rate** | `No of AV's / AVG lifespan` | Vehicles/Year |
| **Renewable capacity addition rate** | `Base Renewable Growth Rate * (1 + Effect of AV on investment)` | MWh/Year |
| **Renewable capacity decommission rate** | `Installed renewable capacity / Renewable plant lifespan` | MWh/Year |
| **Electricity Demand from AV** | `No of AV's * AVG energy consumption` | MWh/Year |
| **time increment** | `1` | Year |

| Auxiliary Variable Name | Equation | Units |
|---|---|---|
| **Adoption saturation** | `1 - EXP(-0.1 * AV market share)` | **undefined** |
| **Annual Lithium demand** | `AV adoption rate * lithium per battery` | Kg/Year |
| **AV attractiveness factor** | `(AV technology advancement rate + Charging infrastructure sufficiency + Government Incentive) / 3` | **undefined** |
| **AV market share** | `MIN(0.8, 0.05 + (Simulation time/10) * (AV attractiveness factor/10))` | **undefined** |
| **AV technology advancement rate** | `0.2` | **undefined** |
| **AVG energy consumption** | `4` | MWh/Vehicles |
| **AVG lifespan** | `15` | Year |
| **Base Renewable Growth Rate** | `1e+06` | MWh/Year |

| | | |
|---|---|---|
| **Charging infrastructure sufficiency** | 7 | **undefined** |
| **Effect of AV on investment** | 0.2 + 0.25 * (Renewable supply gap / (0.1 * Installed renewable capacity)) | **undefined** |
| **global lithium supply** | 500000 | Kg/Year |
| **Government Incentive** | MAX(10, original incentive * (1 - 0.5 * shortage1)) | **undefined** |
| **lithium per battery** | 50 | Kg/Vehicles |
| **market resistance** | 0.2 + 0.8 * (1 - Adoption saturation) | **undefined** |
| **original incentive** | 7 | **undefined** |
| **Renewable plant lifespan** | 15 | Year |
| **Renewable supply gap** | MAX(0, Total Electricity demand - Installed renewable capacity) | **undefined** |
| **shortage ratio** | MAX(0, (Annual Lithium demand - global lithium supply) / global lithium supply) | **undefined** |
| **shortage1** | DELAY FIXED(shortage ratio, 1, 0) | **undefined** |
| **Total Vehicle market share** | 1.75e+06 | Vehicles/Year |

# Analysis from the Model

The stock-flow model helps us understand the dynamic relationship between AV adoption, resource availability, and energy infrastructure. Key insights include:

- AV Adoption increases with government incentives and charging infrastructure but is limited by lithium availability and saturation levels.
- Electricity Demand rises as AVs increase, and if renewable energy growth is insufficient, it leads to an energy supply gap.
- Lithium Demand grows sharply with AV production, and a shortage can slow down further adoption.
- The model reveals critical feedback loops:
    - Reinforcing loop: More AVs → better infrastructure → more AVs.
    - Balancing loop: More AVs → more lithium use → shortage → slower AV growth.
- Scenario simulations show that balanced policy and investment in AVs and renewables is essential for long-term sustainability.

## Simulations and Insights

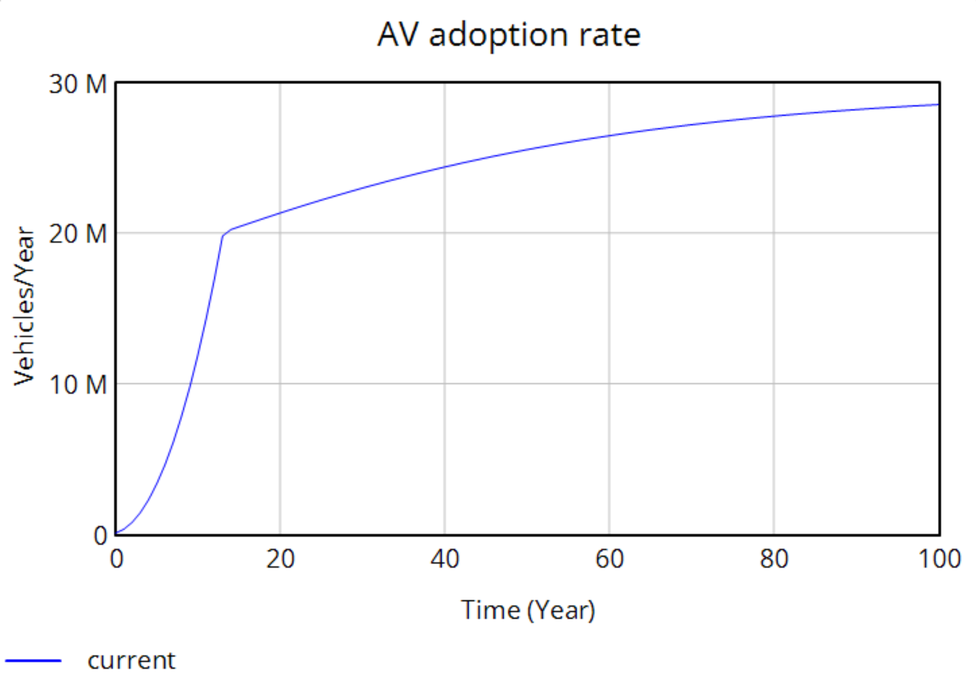
### 1. AV Adoption Rate (Vehicles/Year)

Observation:

- Rapid initial rise (steep slope until ~Year 15)
- Then gradually tapers off, approaching ~30 million/year

Analysis:

- Early aggressive adoption due to incentives, tech growth, and infrastructure.
- Adoption saturates as market gets filled and resistance kicks in.
- Reflects market saturation and possibly lithium or infrastructure limitations.



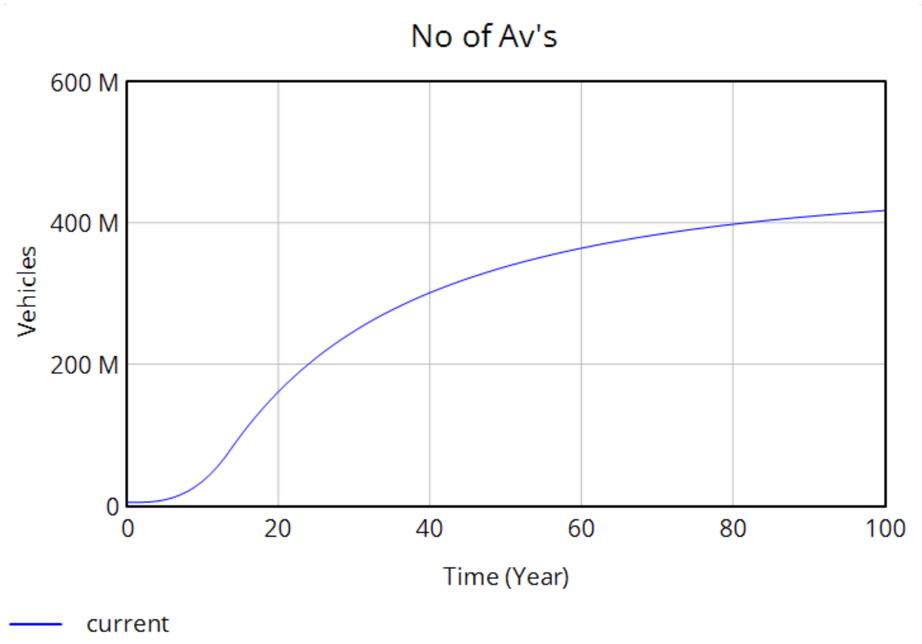

### 2. Number of AVs (Total Vehicles)

Observation:

- Follows an S-curve.
- Steady rise for first 40 years, then flattens toward ~450 million AVs.

Analysis:

- Accumulation effect from consistent yearly adoption.
- Reflects stock dynamics—growth slows as retirements balance new additions.
- Also constrained by lithium and policy factors.



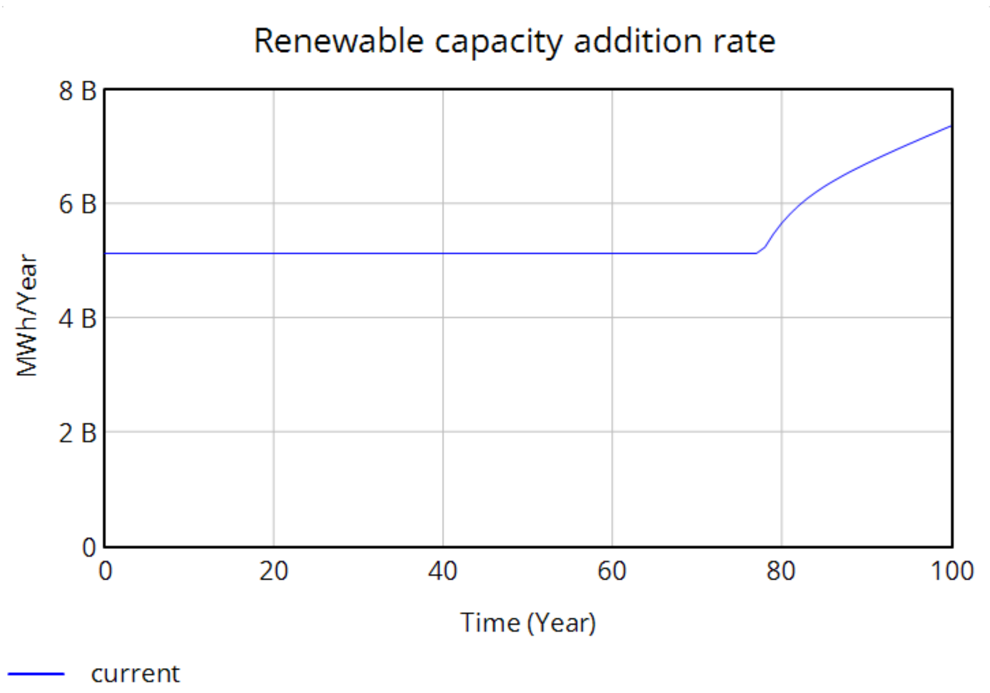

## 3. Renewable Capacity Addition Rate (MWh/Year)

Observation:

- Flat until ~Year 75, then increases steeply.

Analysis:

- Early years: Base growth rate only.
- After Year 75: Effect of AV demand kicks in → increases investments.
- Reflects a delayed policy or market response to growing electricity demand.



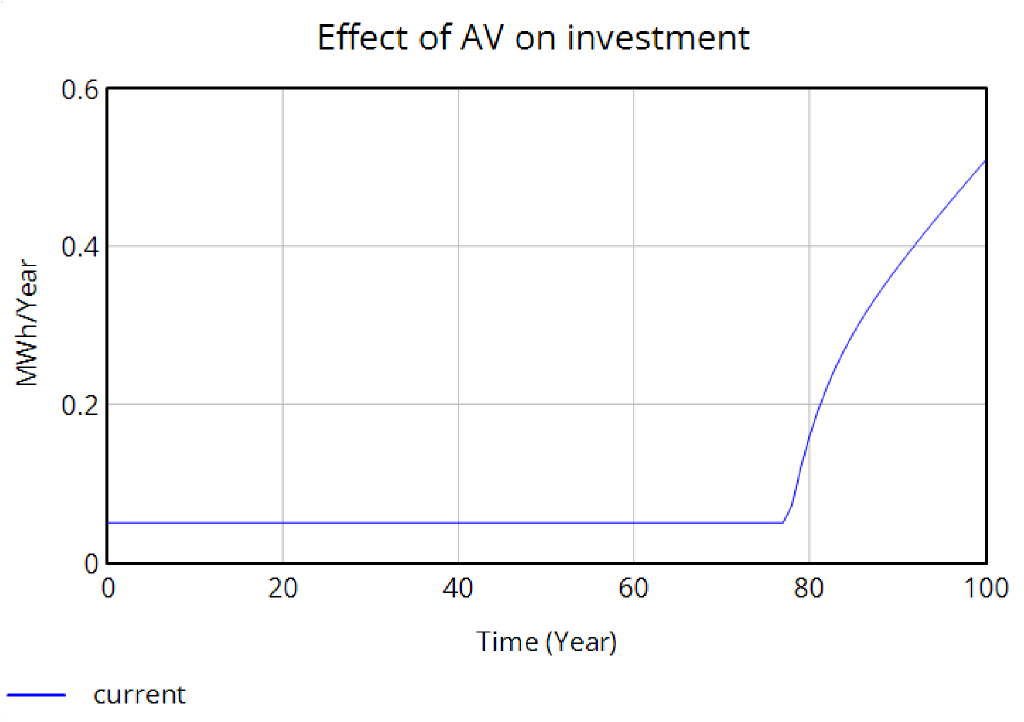
## 4. Effect of AV on Investment (MWh/Year)

Observation:

- Constant for a long period, sharp rise starts ~Year 75

Analysis:

- Investment behaviour doesn’t react instantly.
- Highlights a lag in energy planning—response only comes after high electricity demand becomes critical.



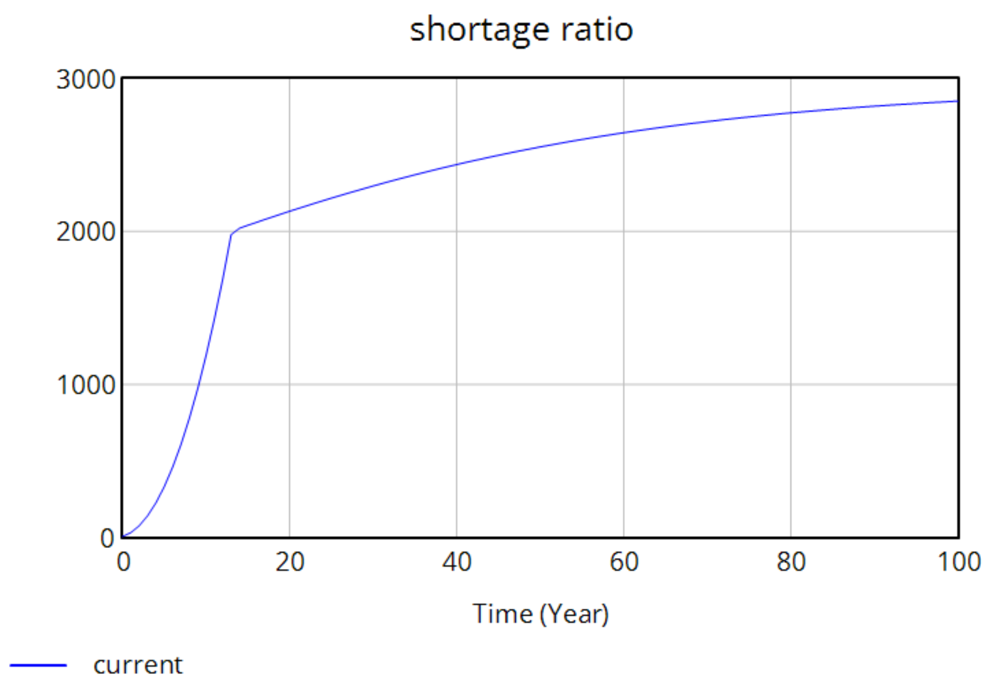

## 5. Shortage Ratio (Lithium Demand/Supply)

Observation:

- Steep rise early on, reaching ~2000 by Year 20, continues slowly increasing to ~2800

Analysis:

- Indicates severe lithium shortage throughout.
- Lithium demand is many times higher than global supply.
- Reinforces a key balancing loop → likely slows future AV adoption.
- Urgent need for solutions like recycling or alternate battery chemistries.



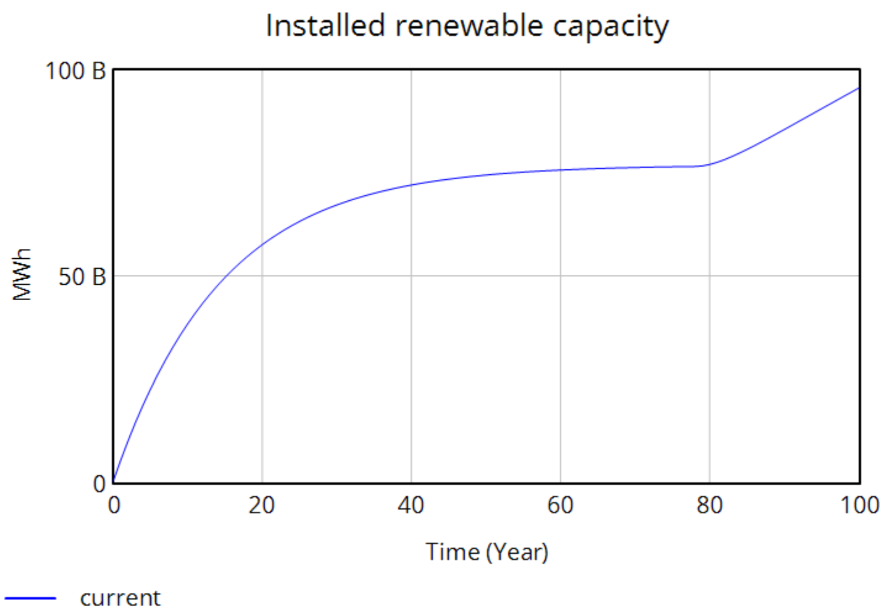

## 6. Installed Renewable Capacity (MWh)

Observation:

- Steep initial growth, plateaus around Year 70, then increases again.

Analysis:

- Early investment grows base capacity well.
- Mid-term slowdown possibly due to aging plants (decommissioning).
- Later growth driven by delayed AV-induced investment.
- Reflects the need for continuous policy support and reinvestment.



### Summary of Insights

- Early adoption of AVs is strong, but resource (lithium) shortages emerge quickly.
- Electricity demand grows, but renewable capacity doesn't initially keep pace.
- There's a delay in investment response to AV-induced electricity pressure—potentially causing future energy gaps.
- The lithium shortage is the biggest red flag, requiring attention for scaling AV production sustainably.
- The system naturally balances itself through saturation and resource limits, which is a core reason for using simulation over static analysis.

## Conclusion

In conclusion, our system dynamics model effectively illustrates the interconnections between automobile adoption, fossil fuel consumption, and electricity demand. The simulation outcomes underscore the potential environmental trade-offs that arise from increased vehicle usage, particularly in the context of transitioning toward electric vehicles. As our model evolves over time, we observe feedback loops, delays, and non-linearities that play a critical role in determining the sustainability of such a transition.

One of the key insights from this project is the recognition that the system we are modelling is inherently **dynamic and non-linear**. Unlike static tools such as Excel, which are limited to linear, snapshot-based analysis, our model incorporates time-based dependencies, interlinked variables, and feedback mechanisms that cannot be accurately captured or visualized in spreadsheets alone.

This complexity is precisely why a **Digital Twin approach** is essential. A digital twin does not merely simulate a system—it enables real-time monitoring, scenario testing, and strategic decision-making based on the evolving state of the system. By using Vensim, we have laid the groundwork for such a digital twin, providing stakeholders with a powerful tool to test policies, anticipate outcomes, and support sustainable transportation planning in an increasingly complex energy landscape.

Going forward, refining the model with more granular data and real-time inputs could enhance its predictive power and decision-support capabilities—bringing it even closer to a fully functional digital twin.