

**Yes — but do NOT build your own physics engine from scratch.** That would be a multi-year, multi-million-dollar effort (think the scale of Ansys, dSPACE, or IPG CarMaker teams). Automotive physics simulation is an extremely mature field with battle-tested open-source engines that already outperform what a small team could build in reasonable time/budget.

Instead, **extend an existing SOTA open-source physics simulator** — this is exactly how top labs and companies (Waymo, Tesla, Uber ATG, etc.) generate synthetic diagnostics data today.

## **Best Options for Your Use Case (2026)**

| Simulator                                     | Why It's Perfect for Diagnostics   | Fault Injection Ease                        | Open-Source?                         | Fidelity Level                              | Key Links  |
|---|--|---|--------------------------------------|---|--|
| <b>Project Chrono</b><br>(top recommendation) | Multi-body vehicle dynamics + deformable terrain + sensors + fluids + FEA. Excellent for engine/transmission/wheel faults, OBD-like signals. Used by NIRA Dynamics for real diagnostics pipelines. | Very easy (template-based + Python/C++ API) | Fully open (Apache 2.0)              | Very high (validated against real vehicles) | <a href="#">projectchrono.org</a><br><a href="#">Chrono::Vehicle</a> |
| <b>CARLA</b>                                  | Urban driving + perfect sensor sim (LiDAR, camera, IMU, CAN/OBD export) + already used for massive synthetic datasets.   | High — community fault plugins exist        | MIT                                  | High for perception + dynamics              | <a href="#">carla.org</a>  |
| <b>BeamNG.tech</b>                            | Hyper-realistic soft-body vehicle deformation + crashes + tire physics. Great for structural/suspension faults.  | Excellent (Lua scripting for faults)        | Academic license (free for research) | Highest for vehicle damage                  | <a href="#">beamng.tech</a>  |
| <b>Open-Car-Dynamics (TUM)</b>                | Lightweight multibody ODE-based vehicle model. Perfect for quick trajectory + controller testing.  | Easy  | Apache 2.0                           | Medium-high                                 | <a href="#">github.com/TUM-Car-Dynamics</a>                          |

## How to Generate World-Class Synthetic Diagnostics Data (Step-by-Step)

### 1. Choose base simulator

Start with **Project Chrono** (best balance of fidelity + extensibility for engine/OBD faults).

## 2. Add fault injection (this is the key part for diagnostics)

```
Python

# Example using Chrono Python API (or C++)
import pychrono as chrono
import pychrono.vehicle as veh

# Create vehicle
vehicle = veh.WheeledVehicle(...)

# Inject faults
def inject_fault(t):
    if t > 100: # e.g., after 100s
        # Sensor drift (O2 sensor)
        vehicle.GetSensor("O2").AddNoise(0.15) # 15% bias
        # Actuator failure (throttle stuck)
        vehicle.GetActuator("throttle").SetStuck(0.8)
        # Engine misfire
        vehicle.GetEngine().SetMisfireRate(0.3)

# Run simulation loop with fault callback
```

Common faults to simulate:

- Sensor: drift, noise, stuck, dropout (MAF, O2, coolant temp, etc.)
- Actuator: stuck, delayed, partial failure
- Mechanical: tire puncture, suspension wear, bearing failure
- Electrical: short/open circuit, ECU glitch

## 3. Export OBD-II style data

Log exactly what real OBD tools see: PID values (RPM, speed, temps, pressures, DTCs, freeze-frame). Chrono/CARLA can output CAN/OBD-compatible logs.

#### 4. Scale to millions of examples

- Domain randomization: vary vehicle models, weather, road conditions, manufacturing tolerances.
- Run on GPU cluster → generate 10M+ labeled traces in days.
- Use teacher models (o1-pro / Claude-3.7) to generate diagnostic reasoning traces on top (like OpenThoughts3 style).

#### 5. Bridge sim-to-real gap (critical for production)

- Add realistic sensor noise models (from real OBD datasets you already have).
- Fine-tune final ML model on 10% real + 90% synthetic (standard sim-to-real recipe).
- Physics-informed ML: embed Chrono equations directly into your neural net (via NeuralPDE or DiffSim).

### Proof This Works (Recent Research)

- NIRA Dynamics (real automotive company) replaced their Simulink models with Chrono for diagnostics testing — huge maintenance win.
- Papers show physics-sim + ML beats real-data-only on fault detection (e.g., SEAD method, hybrid physics-ML ensembles).
- CARLA/BeamNG used successfully for OBD-style anomaly detection datasets.

**Bottom line:** Building your own physics engine = 5+ years and \$10M+. Extending Chrono/CARLA = 1–3 months to first 1M labeled examples, then iterate.

If you want, I can give you a full starter repo template (Chrono + fault injection + data export pipeline) or help pick the exact faults to simulate first based on your target vehicles. What's your priority — engine faults, EV battery, or full vehicle?