Intelligent Control Technique in Electric Vehicles – part 1

Battery research and development, battery management, range estimation

Nataša Popović, PhD

1. Introduction

- ✓ With the growing awareness of climate change and the depletion of fossil fuels, the demand for environmentally friendly transportation options is increasing.
- ✓ Electric vehicles (EVs) represent a key player in this positive shift, using electric energy instead of traditional fuels.
- ✓ With zero harmful gas emissions, electric vehicles offer a “cleaner” alternative compared to conventional cars.
- ✓ However, despite the positive outlook of EV integration in society, EVs still face challenges to their widespread adoption.
- ✓ These challenges include EVs’ limited range and the associated user range anxiety, lack of charging infrastructure, the high upfront cost of EVs compared
- ✓ with that of traditional internal combustion engine vehicles, and safety concerns.
- ✓ Therefore, developing related novel techniques and proposing useful strategies are necessary to overcome those challenges.

1. Introduction

- ✓ Artificial intelligence (AI), which is defined as algorithms supporting models aimed at mimicking natural thinking, perception, and action, has seen industrial and academic applications in the field of EVs and related infrastructures, such as in:
  - EV battery design and management,
  - charging stations,
  - the smart grid.
- ✓ AI algorithms usually utilized in EVs are:
  - machine learning (ML),
  - computational intelligence (CI).
- ✓ Depending on the problem, these AI algorithms can outperform classical rule-based systems (also called expert systems), which uses human knowledge to define rules within a system.

1. Introduction

✓ Several advantages of AI application include:

- EV cost reduction through optimal battery-material design and manufacturing,
- accurate range estimation to mitigate EV consumer range anxiety by predicting future driving conditions,
- improved EV energy consumption versus traditional controls using AI controls for the EV auxiliary systems,
- a potential for increased road safety and optimal traffic flowthrough connected and autonomous driving,
- a thorough and efficient modeling approach for optimal location and resource allocation for electric vehicle charging stations (EVCSs) and energy scheduling for EV interaction with the smart grid.

2. AI techniques in EVs

Machine learning

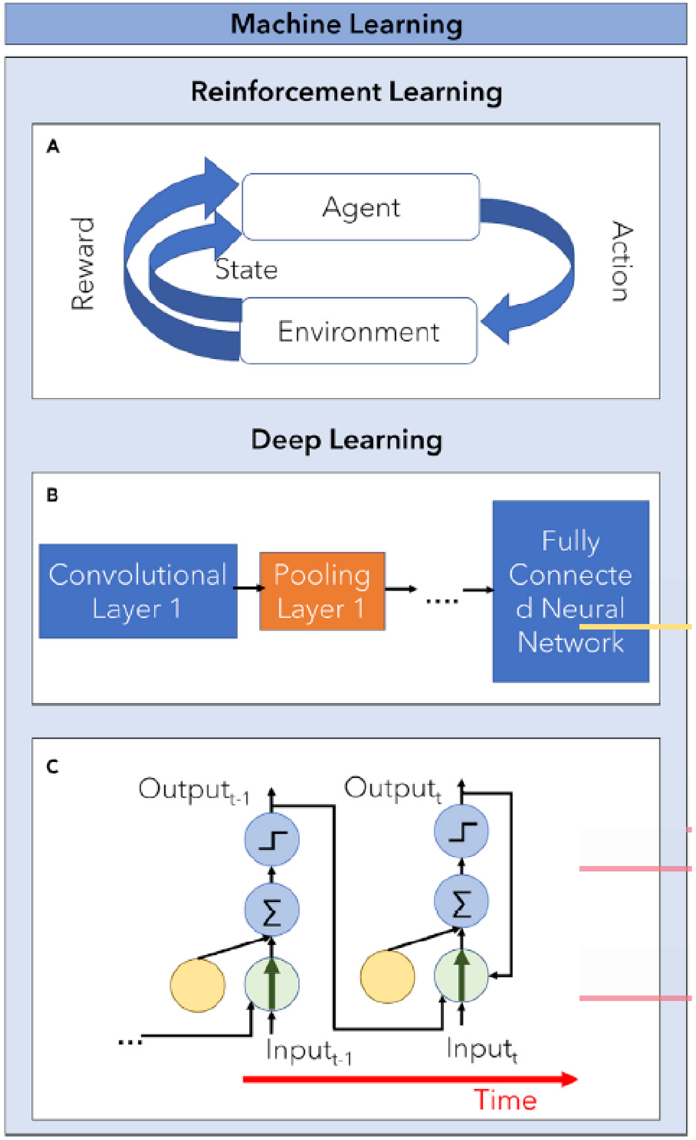
- ✓ ML models are adept at finding relations and trends between inputs and outputs based on previous observations, and they require training on a previous dataset.
- ✓ The ML used in EVs and related infrastructures can be roughly classified:
    - supervised,
    - unsupervised,
    - reinforcement learning (RL).
- ✓ The supervised and unsupervised learning have been researched and applied in areas within EV and its infrastructure where large datasets are available or can be created, such as in EV battery-state estimation and discovery of new materials for EV batteries.
- ✓ Their basic concepts are displayed through deep-learning (DL) model uses architectures involving neural networks (NN) with more than one hidden layer; and RL learning the best course of action on its own through trial and error, and the agent interacts with its environment through actions and is rewarded accordingly.

2. AI techniques in EVs

- ✓ Process flow for reinforcement learning: The agent interacts with the environment and gains a reward accordingly based on its action. Through iterative learning, the agent learns and adopts a policy that aims to maximize its reward.

- ✓ Deep learning: CNN (convolution neural networks), commonly used for image processing, as successive layers of convolutional and pooling layers are connected to a fully connected neural network. Convolutional layers filter the image based on high-level image features while the pooling layer compresses the image to reduce its size for ease of handling.

- ✓ Neural network of recurrent neural networks (RNN). RNN, commonly used for time series analysis, has the output of the neural network at (t-1) timestep as the input of the at t time-step. The image shows a single RNN unrolled in time.



2. AI techniques in EVs

Computational intelligence

✓ Computational intelligence algorithms are commonly used for solving search, optimization, and other complex problems.

✓ The CI used in EVs and related infrastructures can be roughly classified:

- swarm intelligence,
- genetic algorithms.

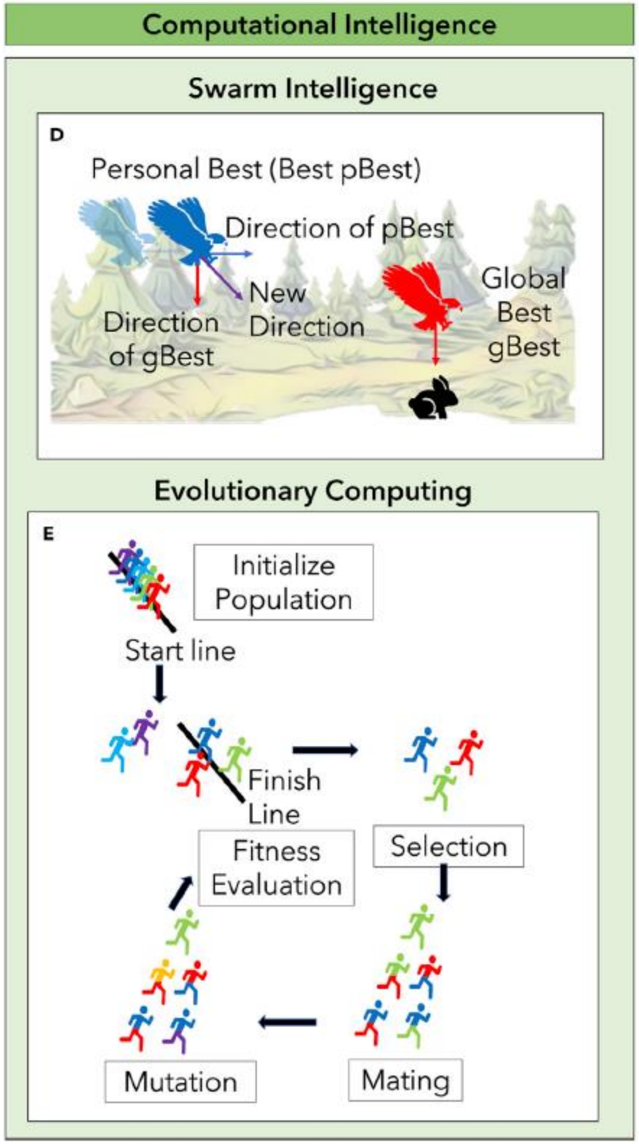
✓ Within the EV context, CI algorithms are instrumental in solving complex, dynamic optimization problems, such as:

- optimization of control systems within EVs,
- optimal placement of EVCSs,
- Integration of EV infrastructure with the smart grid.

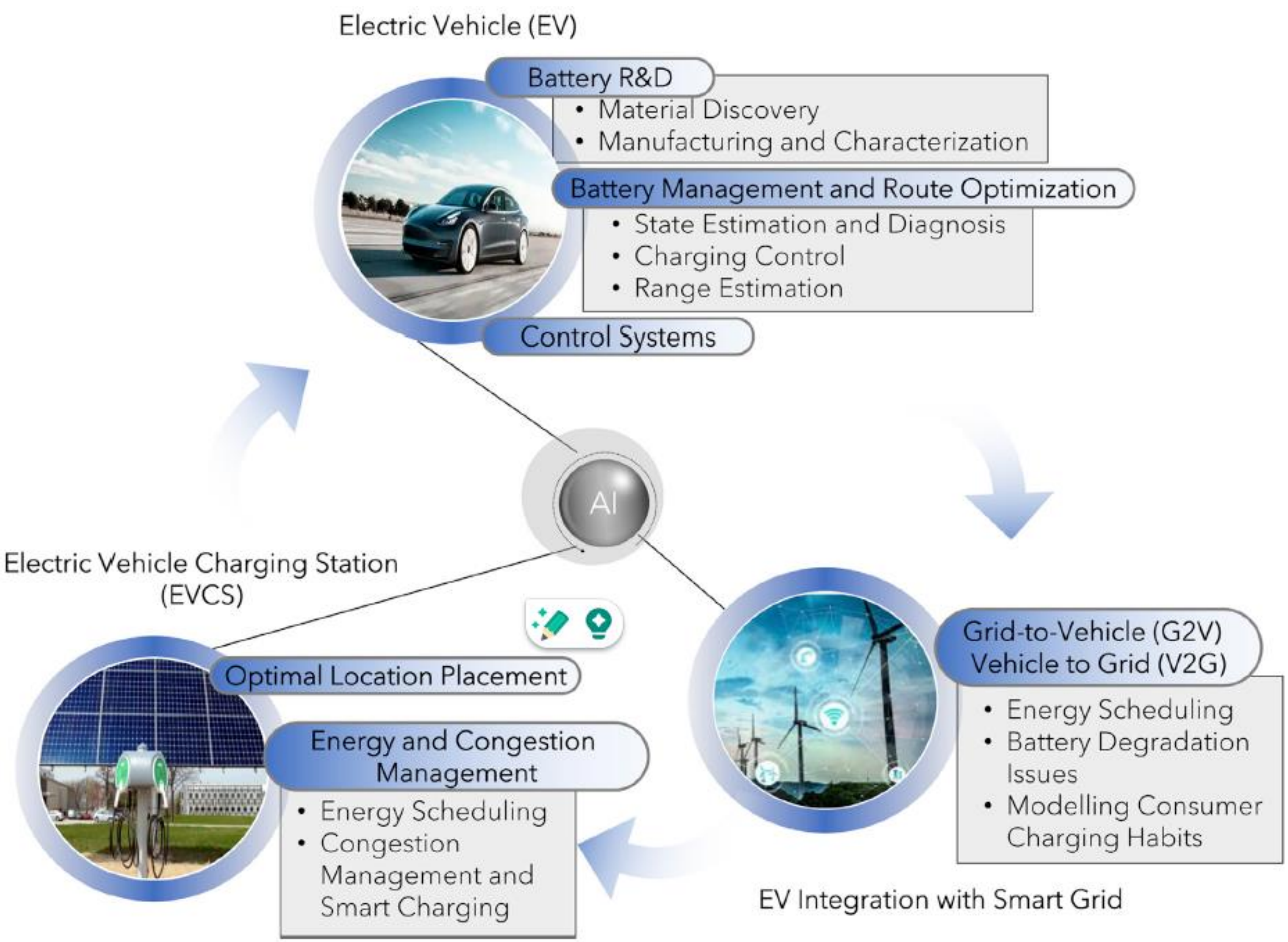
2. AI techniques in EVs

- ✓ Process flow of particle swarm intelligence (PSO): PSO, commonly used for search and optimization engineering problems, has a swarm of particles, which search in the solution space. The particles communicate both a particle's personal best and the global best to find the solution.

- ✓ Process flow of genetic algorithm (GA). GA, commonly used for search and optimization engineering problems, has an initial population of solutions. During each iterative process, the population undergoes mutation and crossover operations to find the solution.



2. AI techniques in EVs



3. ML in battery research and development

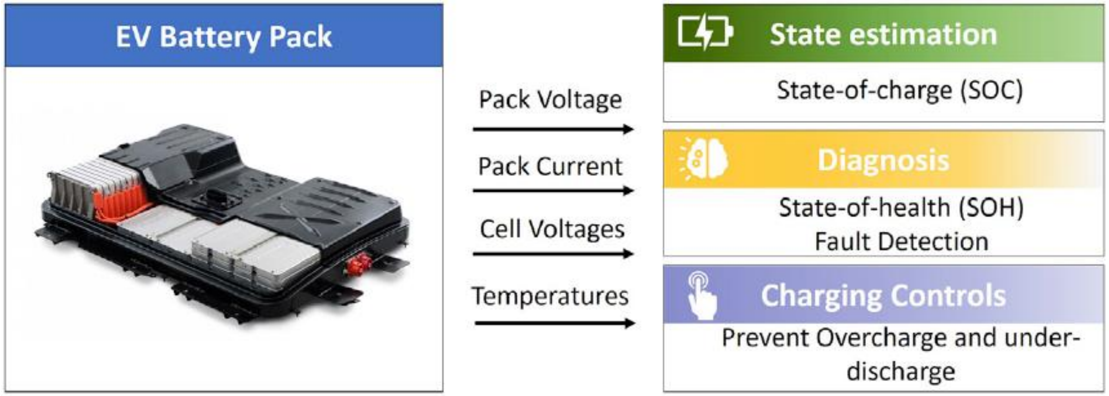
- ✓ Limitations in battery design and manufacturing lead to lower energy-density of the EV battery pack, resulting in increased cost.
- ✓ To achieve higher energy efficiency, consumer perception, safety, and economic feasibility, ML techniques to overcome the above challenges have received increased academic and commercial attention.
- ✓ Applications:
  - battery-material discovery and characterizations,
  - exploring new material discovery of higher energy density and safer battery electrodes, solid electrolytes, and electrolyte additives,
  - for complex molecular interactions, reaction pathways, and minimization of side reactions,
  - to predict the anticipated properties of new materials from other known properties,
  - electrochemical impedance spectroscopy, cycle-life testing, and tomography,
  - to predict the electrode mass loading from control parameters involved in slurry mixing (mass content, solid-to-liquid ratio, and slurry viscosity) and coating onto the substrate,
  - to predict the charge-discharge specific resistance from the electrode porosity features (porosity, active material particle size and volume fraction, and compaction process pressure), electrolyte conductivity, and binder/additive volume fractions.

4. ML in battery management

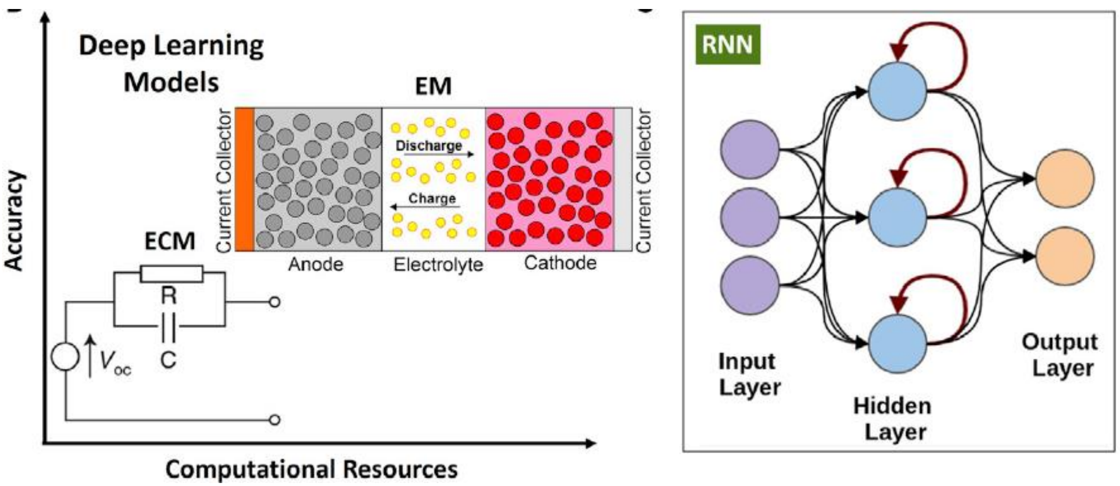
- ✓ Battery-management system (BMS) is responsible for battery-pack sensing, battery-state estimation, and diagnosis and ensures energy-efficient control of the EV battery pack.
- ✓ ML-based state estimation can be used in EVs because of its lower computational demand, accuracy, and lack of need for extensive mathematical models.
- ✓ Applications:
  - state-of-charge (SOC),
  - and state-of-health (SOH),
  - battery-fault detection (overcharge, overdischarge, extreme temperature exposure, faulty external connections, and mechanical damage),
  - general regression neural network (GRNN) has been employed for fault detection with a high accuracy (>95%),
  - to find trends between the cause and consequence of a battery fault by using datasets from experiments and physical models

4. ML in battery management

- ✓ The battery-pack sensor input information to the battery-management system: The battery management system collects the time series data, consisting of pack voltage, pack current, voltages of individual cells, and temperatures from the temperature probes at intervals.

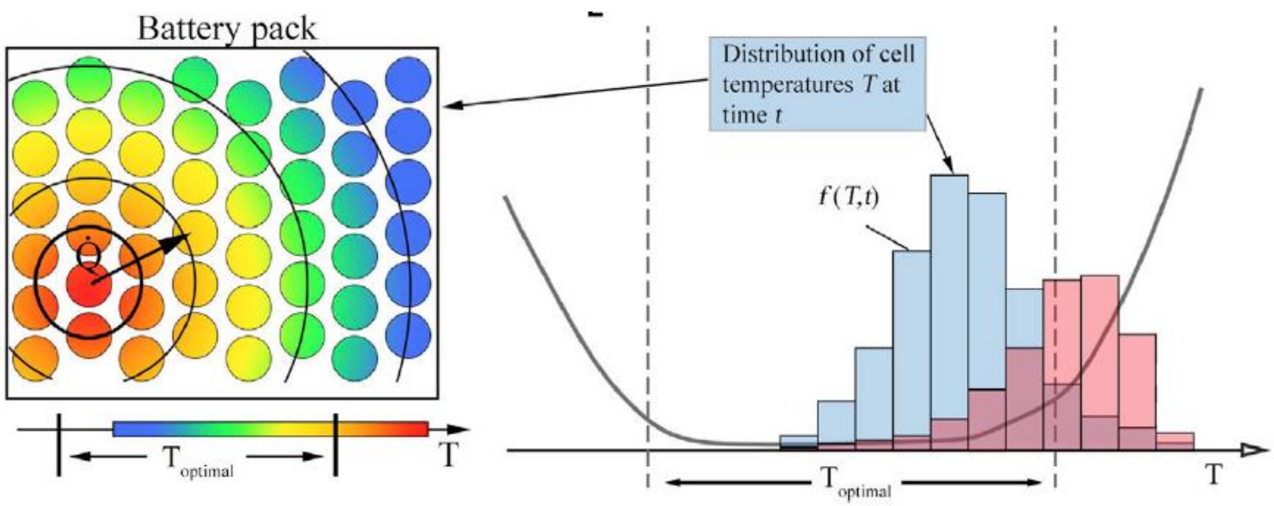


- ✓ Accuracy versus computational resources required for SOC and SOH estimation: When measuring SOC and SOH, data-driven models, powered by deep learning algorithms, show higher accuracy than the ECM models and much lower computational resources compared with physical models, such as single-particle models.



4. ML in battery management

✓ The temperature profile of the battery cells in a battery pack. The temperature profile of the batteries can be visualized as a histogram. The temperature variation can be trained by using an RNN to predict the future temperature values, which can be compared with actual values for anomalies.



5. ML in range optimization

Table 2. Representative research of machine learning (ML) in EV range estimation (RE)

Approach	Parameters	ML algorithm	RE accuracy
Historical data	battery SOC voltage (min, max) current (min, max) temperature (min, max) vehicle speed (avg) external temperature visibility precipitation	significant parameter identification using correlation analysis followed by multiple linear regression (MLR)	1.63 km (MAE)[106]
		classification and regression tree (CART)	1.27 km (MAE)[98]
		gradient boosting decision tree (GBDT)	0.82 km (MAE)[98]
	battery SOC SOH vehicle auxiliary load weight external road type traffic temperature driving behavior	artificial neural networks (ANN)	2.2% (MSE) accuracy for a 50.4 km real-life EV trip[103]
Predicting future energy/power consumption	Vehicle speed recent energy consumption external road elevation	linear regression (LR)	2.18 km (MAE)[105]
		support vector regression (SVR)	1.95 km (MAE)[105]
	vehicle speed acceleration past power consumption past distance past trip run time temperature weight of loads tire pressure frontal area external road elevation	MLR	1.95 km (MAE)[104]
		principal component regression (PCR)	2.07 km (MAE)[104]
		clustering of data using self-organizing maps (SOM) followed by regression tree	0.70 km (MAE)[104]

Abbreviations are as follows: MAE, mean absolute error; MSE, mean-squared error.