ALGAV Report – Sprint C

State of the Art of the use of Machine Learning technologies applied to the Distribution Management problem

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Machine learning is an area of computing that has been widely used in delivery systems to improve the efficiency, accuracy, and speed of these systems. Some examples of machine learning applications in delivery systems include:

1. Detecting False-Positive RFID Tag Reads in Transport Management:

Several variables, including the picking procedure and the allocation of pallets to specific trucks, affect the likelihood of an error-free shipment. The antennas of the portals have ranges of several meters and therefore identify all pallets in range, pallets to be shipped and pallets placed for intermediate storage. In order to differentiate between the moving and static pallets, METRO Group Cash & Carry applied ML techniques based on the recorded attributes by each pallet. It was observed that, depending on the frequencies transmitted to the portals, the tags of static and moving pallets submit varied RSSI values. This is where ML comes into play because it is a well-known ML problem to classify two attributes based on their threshold value. For the training phase of machine learning, a very big data collection is needed to automatically evaluate the properties. All 70 loading ramps had RFID gateways inserted by the distribution center, which then kept track of them for 7 months. A total of 53,998 pallets were seen, of which 13,245 were moved via the outgoing goods gateway and 40,743 were static. After the data gathering process was complete, the used algorithm was able to classify more than 95.5% of the data accurately. As a result, false-positive pallets can be directly recorded while the pallets can be quickly identified. Faulty inventory adjustments and deliveries were reduced as a result.(Reads & Keller, 2010)

2. Demand forecast for Distribution Management:

Often, stores require products to be delivered within a short period of time, yet manufacturers have relatively long lead times. To solve this problem, weekly demand estimates based on SKU (stock keeping units) level are generated over a period of six months using artificial intelligence algorithms. Data from a distribution center's last 2.5 years were utilized to train the algorithm, and the seasonality element was taken into consideration.

The artificial intelligence algorithms improved the demand estimates during a six-month period to the point where it was possible to significantly enhance forecast quality, allowing industrial partners to plan far earlier. Thus, it is possible to considerably improve delivery dependability and product availability, which is facilitated by an automated information flow of future demand to industrial partners. Through accurate projections, the industrial partners can rely on better planning and ordering security, while the store chain can rely on secure product supply and fewer surplus stockpiles. Customers are happy as a result, and expenses are reduced.(Mohamed-Iliasse et al., 2022)

3. Operating Electric Vehicle Fleet for Ride-Hailing Services With Reinforcement Learning:

This application is related to the use of machine learning for route management by building an RL (reinforcement learning) based algorithm to dispatch an electric vehicle fleet for ride-hailing services. The suggested RL-based algorithm, which was created in 2019, is based on a novel paradigm that includes centralized learning and decision-making components. The decentralized learning component allows the whole EV fleet to share their experiences and approximate state value function parameters throughout the training phase, boosting the algorithm's scalability. The centralized decision-making mechanism allows for the coordination of individual EVs, maximizing the EV fleet's action value function.

“The results of the simulation, developed to evaluate the maturity of the system, show that the RL agent quickly learns how to dispatch an EV fleet to provide ride hailing services. The proposed RL algorithm outperforms the benchmark algorithms in terms of social costs, which include EV operational costs and customer waiting time.”(Shi et al., 2020)

4. Electric vehicle routing problem with machine learning for energy prediction:

The machine learning application is concerned to the time-dependent Electric Vehicle Routing Problem with Chance-Constrained (EVRPCC) partial recharging.

The main contributions are:

1. a machine-learning-enabled probabilistic energy consumption model that can calculate the variance and predicted energy of road linkages, pathways, and routes;
2. a two-stage routing model that uses chance restrictions to arrange partial recharging while incorporating energy prediction;
3. numerical tests to verify and analyze the model properties under plausible conditions.

In a study conducted in 2020, with energy estimation validated with data from electric buses driving a public transport route in Gothenburg-Sweden as well as with realistic simulations for 24 hours traffic in the city of Luxembourg, main results can be summarized as follows:

- Even with inaccurate speed forecasts, the accuracy of the energy consumption estimation led to a mean absolute percentage error of less than 6%. After just a few journeys are driven from the depot to the intended consumer region, the forecast quickly improves.
- As the model gains experience from more data, the variance it predicts tends to decrease, suggesting that it improves in precision with time. In the experiments, no actual consumption occurred outside of the prediction's 95% confidence zone.
- For the 100 routes without charging, an average energy savings of 10.6% was possible (with a maximum savings of 19.5%).
- By ensuring that the battery level would not, with a certain degree of confidence, go below the minimal level, the reliability of the charge planning is significantly improved.

There are numerous approaches to expand the model. Future research could include testing and modifying it for use with combustion engines and other vehicle architectures. Further research and incorporation into the machine learning and routing models can be done on the correlation of the energy usage for nearby road connectors. The model should be used to a dynamic vehicle routing problem to anticipate energy and reroute in real-time, as energy is dependent on dynamic factors like congestion and unpredictable events like accidents.(Basso et al., 2021)

References

Basso, R., Kulcsár, B., & Sanchez-Diaz, I. (2021). Electric vehicle routing problem with machine learning for energy prediction. *Transportation Research Part B: Methodological*, *145*, 24–55. https://doi.org/10.1016/j.trb.2020.12.007

Mohamed-Iliasse, M., Loubna, B., & Abdelaziz, B. (2022). Machine Learning in Supply Chain Management: A Systematic Literature Review. In *International Journal of Supply and Operations Management* (Vol. 9, Issue 4). www.ijsom.com

Reads, F. R. T., & Keller, T. (2010). Using Low-Level Reader Data to Detect. *IEEE*, *7*.

Shi, J., Gao, Y., Wang, W., Yu, N., & Ioannou, P. A. (2020). Operating Electric Vehicle Fleet for Ride-Hailing Services with Reinforcement Learning. *IEEE Transactions on Intelligent Transportation Systems*, *21*(11), 4822–4834. https://doi.org/10.1109/TITS.2019.2947408

Shen, H., Engineering, C., & Wang, J. (2022). Longitudinal Slip Ratio and Machine-Learning-Based Powertrain Efficiency. *IFAC PapersOnLine*, *55*(37), 158–163. https://doi.org/10.1016/j.ifacol.2022.11.177