

**IMPROVING EFFICIENCY OF CURRENT ROUTE OPTIMIZATION
ALGORITHMS FOR BEVERAGE DELIVERY TOUR PLANNING**

By

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STATEMENT BY THE AUTHOR

I hereby declare that this submission is my own work and to the best of my knowledge, it contains no material previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any other degree or diploma at any educational institution, except where due acknowledgement is made in the thesis.



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ABSTRACT

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This study explores two ways to make beverage delivery routing more reliable under strict time windows. In the first approach, we use an ARIMA model to forecast travel-time deviations for each leg of a tour, then incorporate those forecasts into Google OR-Tools as penalty adjustments. In the second approach, we train a supervised LSTM network on historical stop sequences enriched with simple temporal features such as day of week and start time, and use its predictions to guide the solver toward more natural stop orders. When testing the ARIMA-enhanced solver across hard-cap, soft-cap, and weighted-cost settings, its performance fell short of the original time-only optimizer, with accuracy dropping from 60.02 percent to 57.25 percent. In contrast, the LSTM model (after fifty epochs of training) achieved a 68.95 percent exact-match rate and 82.89 percent partial-correctness. These findings show that even through the addition of basic contextual signals, combined with features like sequence learning, can significantly improve stop-order prediction. These results show that there are clear benefits to pairing machine learning with traditional routing algorithms to boost delivery consistency and overall efficiency.

Keywords: Vehicle Routing Problem with Time Windows (VRPTW), AutoRegressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), Google OR-Tools, Route Optimization.



DEDICATION

This work is dedicated to my loving mother and late father.



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