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Development environments for route based functions in road vehicles

Master's thesis in Master Programme Mobility engineering

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Cover: Animation from IPG Truckmaker simulation where the test truck is driving on E6 from north turning onto RV40 using Here Technology data

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Abstract

The electrification of heavy vehicles has increased demands on accurate range estimation to support efficient transport planning and reduce range anxiety. Consequently, route-based predictive energy estimation has become an important tool for improving the reliability of range predictions. The energy consumption of heavy vehicles is strongly influenced by factors such as vehicle mass, route topography, traffic conditions, and driving behaviour.

This thesis investigates a predictive range estimation development environment for battery-electric heavy vehicles using a Kalman filter-based energy estimator integrated with TruckMaker simulations and MATLAB-based post-processing. The estimator combines route, weather, and mission information to predict battery energy consumption, state of charge (SOC), and remaining driving range together with its associated variance along a predefined route between the Port of Gothenburg and Viared.

The accuracy of the estimator was evaluated by comparing predicted vehicle behaviour with TruckMaker simulation results. In addition, the influence of re-estimation frequency, vehicle mass uncertainty, and traffic disturbances was investigated. Several distance-based re-estimation intervals were analysed to evaluate how periodic updates affect prediction accuracy. Furthermore, scenarios involving incorrect vehicle mass information, mid-route mass correction, and traffic congestion were introduced to assess the robustness of the prediction framework under changing operating conditions.

The results show that the estimator is capable of predicting SOC and vehicle range with good accuracy under nominal conditions. Periodic re-estimation significantly improves prediction accuracy and enables the estimator to adapt to changing operating conditions throughout the route. Vehicle mass was identified as one of the most influential parameters affecting prediction accuracy, while the investigated traffic disturbance had a comparatively smaller impact on the overall energy consumption. The driver-related estimator parameters K and $\sigma_{v,\text{ref}}$ were also investigated. Both parameters influenced the predicted mean energy consumption and the associated uncertainty, while updating them to values identified from previously driven data resulted in only minor changes in the SOC prediction. These results indicate that the parameters may be useful for tuning the predicted mean energy demand and its associated uncertainty. Overall, the results indicate that continuous re-estimation can improve the robustness of route-based range prediction for battery-electric heavy vehicles.

Keywords: Predictive range estimation, Route-based energy estimation, Vehicle simulation.

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Victor Andersson, Gothenburg, June 2026

Notation

In this thesis, vectors are denoted by bold lowercase symbols, while scalar quantities are written in italic font. The superscript $\dagger$ denotes the Moore–Penrose pseudoinverse. Subscripts are used to distinguish between predicted, simulated, and reference quantities. The subscript *est* denotes an estimated quantity, while *real* denotes the corresponding value obtained from the TruckMaker simulation. The subscript *ref* denotes a reference quantity used by the predictive estimator. Initial and remaining quantities are denoted by the subscripts *init* and *rem*, respectively.

Energy quantities are denoted by E , state of charge by SOC, vehicle speed by v , longitudinal force by F , and travelled distance by s where applicable.

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1

Introduction

1.1 Background

The electrification of heavy-duty road transport is an important part of the ongoing transition towards a more sustainable transport system. Heavy-duty vehicles represent a significant share of transport-related greenhouse gas emissions. In the European Union, heavy-duty vehicles emitted approximately 203 MtCO₂ in 2023, corresponding to around 20% of total transport greenhouse gas emissions [1]. In response, increasingly stringent CO₂ emission requirements have been introduced for new heavy-duty vehicles in the European Union. The revised EU regulation includes a fleet-wide target of a 90% reduction in CO₂ emissions from new heavy-duty vehicles from 2040 onwards compared with the 2019 reference level [2].

Battery-electric vehicles represent one of the main technological alternatives for reducing emissions from road freight transport. The market for electric trucks has grown rapidly in recent years. According to the International Energy Agency, global electric truck sales more than doubled in 2025 and reached approximately 9% of total truck sales worldwide [3]. Despite this development, the transition to battery-electric trucks still involves several technical and operational challenges. A recent study based on surveys, interviews, and workshops with transport companies in Sweden and Germany identified limited charging infrastructure, range constraints, high investment costs, and economic uncertainty as important barriers to wider adoption [4]. These challenges are particularly relevant for commercial transport, where vehicle utilisation, delivery schedules, and operational reliability are directly connected to profitability.

One important challenge is that the achievable driving range of an electric heavy-duty vehicle cannot be described by battery capacity alone. The energy required to complete a transport mission depends strongly on the conditions encountered along the route. Previous research has shown that factors such as road topography, vehicle speed, acceleration and braking, vehicle mass, payload, and powertrain efficiency can significantly affect vehicle energy consumption [5]. For heavy-duty vehicles, this dependency is particularly important because gross vehicle weight can vary considerably between transport missions. Environmental conditions can further affect the available range. Studies of battery-electric heavy-duty vehicles have shown that temperature, wind conditions, payload, and route characteristics can all influence energy consumption and consequently the achievable driving range [6]. As a result, estimates based only on a constant or historical average energy consumption may not accurately represent the energy required for a specific future transport mission.

The availability of information about the upcoming route creates an opportunity to improve these predictions. Route-based energy estimation uses information about expected future operating conditions rather than relying only on previously observed vehicle behaviour. Road elevation, speed profiles, vehicle and mission information, and other route-related parameters can be incorporated into an energy prediction before the vehicle reaches the corresponding road section. Previous research on electric commercial vehicles has demonstrated that incorporating detailed route information, including topography and speed, can improve energy consumption estimation and support route and charging planning [5]. More recent work has further investigated known-route energy demand prediction using a Kalman-smoother-based framework capable of estimating both expected energy demand and its associated uncertainty [7]. Reliable energy prediction can therefore provide a basis for functions such as residual range estimation, energy-efficient route planning, and other predictive vehicle functions.

However, even when detailed route information is available before departure, the actual operating conditions may differ from the assumptions used in the initial prediction. Traffic conditions may change, vehicle or payload information may be incorrect, and differences between predicted and actual vehicle behaviour can accumulate throughout the route. Prediction uncertainty therefore increases the importance of updating the estimate as new information becomes available during operation. Re-estimation can use the current vehicle state to reduce the influence of previous prediction errors and update the expected energy demand for the remaining route. The ability to study both the initial prediction and its development throughout a transport mission is therefore important when evaluating the practical performance of a predictive range estimator.

Developing and evaluating such route-based functions also requires a suitable development environment. Testing a large number of combinations of routes, vehicle parameters, environmental conditions, and disturbances using physical vehicles alone would require considerable time and resources and would make identical test conditions difficult to reproduce. Simulation-based vehicle development provides a controlled environment in which operating conditions can be systematically modified and repeated. TruckMaker is specifically developed for virtual development and testing of heavy-duty vehicles and combines vehicle, driver, traffic, and road models to enable automated and reproducible virtual test scenarios [8]. Such an environment provides a possibility to evaluate predictive vehicle functions under controlled conditions before moving towards testing in physical vehicles.

Against this background, there is a need for systematic development environments in which route-based functions can be integrated, tested, and evaluated under different operating conditions. In this thesis, predictive range estimation for battery-electric heavy-duty vehicles is used as the primary application for demonstrating such an environment.

1.2 Problem Definition

Accurate prediction of the energy required to complete a future transport mission is challenging because the vehicle's energy consumption depends on several parameters

that may vary both between and during transport missions. Even when information about the planned route is available before departure, differences between assumed and actual operating conditions can result in prediction errors. Incorrect vehicle parameters, unexpected traffic conditions, and differences between predicted and actual vehicle behaviour may therefore reduce the accuracy of the estimated state of charge and remaining driving range.

Route-based predictive energy estimators provide a possibility to account for future operating conditions by combining information about the route, vehicle, environment, and transport mission. However, developing such an estimator is not sufficient on its own. The estimator must also be evaluated in an environment where its predictions can be compared with a representative vehicle response under controlled and repeatable conditions. This is necessary to identify prediction errors, investigate sensitivity to uncertain input parameters, and determine how the estimator responds when operating conditions change during the route.

An additional challenge is that an initial range prediction becomes less representative if the assumptions made before departure no longer correspond to the actual vehicle state. Updating the prediction during the journey can therefore be important. By periodically re-estimating the remaining energy demand using updated vehicle information, accumulated prediction errors may be reduced and changes in operating conditions can be taken into account. The required update frequency and the ability of the estimator to recover from incorrect initial assumptions are therefore important aspects of its practical performance.

Within ongoing research at Chalmers University of Technology, predictive energy estimation methods are being developed for road vehicles. To support the evaluation and further development of such methods, there is a need for a structured development environment in which route-based functions can be integrated with a vehicle simulation model and systematically tested. Such an environment should enable comparison between predicted and simulated vehicle behaviour and allow controlled modifications of vehicle, route, and operating conditions.

The problem addressed in this thesis is therefore how a simulation-based development environment can be established for a route-based predictive range estimator for battery-electric heavy-duty vehicles. Particular attention is given to the accuracy of the predicted state of charge and driving range, the influence of uncertain vehicle and traffic information, and the effect of periodic re-estimation throughout the route. The environment should also enable the influence and adaptation of driver-related estimator parameters, including K and $\sigma_{v,\text{ref}}$, to be investigated.

In addition, the development environment should have the potential to be further extended towards implementation and testing in a physical research vehicle.

1.3 Aim and Objectives

The overall aim of this master's thesis is to develop and demonstrate a simulation-based development and evaluation environment for route-based predictive range estimation in battery-electric heavy-duty vehicles. The environment combines a predictive energy estimator with vehicle simulation in TruckMaker and MATLAB-based post-processing in order to evaluate estimator performance under different

operating conditions. The environment shall support a predictive estimator that provides both an expected energy and range prediction and a measure of the associated prediction uncertainty.

The specific objectives are:

- To establish a modular test environment for route-based predictive range estimation using TruckMaker.
- To integrate relevant route, environmental, vehicle, and mission-specific data required for predictive energy and range estimation.
- To evaluate both the expected prediction and its associated uncertainty by comparing predicted vehicle behaviour with TruckMaker simulation results.
- To investigate the influence of uncertain or changing operating conditions, including vehicle mass and traffic disturbances, on prediction accuracy.
- To investigate how periodic re-estimation influences prediction accuracy throughout a route.
- To identify the driver-related parameters K and $\sigma_{v,\text{ref}}$ from previously driven data and investigate their influence on predicted energy consumption, prediction uncertainty, and SOC.

1.4 Research Questions

To evaluate whether the developed simulation environment fulfils its intended purpose, it should enable systematic evaluation of the predictive estimator under different operating conditions. The following research questions are therefore addressed:

1. How accurately can predictive range estimation methods perform within a structured simulation and validation framework under varying operating conditions?
2. Which inputs and assumptions have the largest impact on range estimation accuracy and robustness?
3. How does re-estimation frequency influence the accuracy of predictive range estimation throughout a route?
4. How do the driver-related estimator parameters K and $\sigma_{v,\text{ref}}$ influence the predicted energy consumption, state of charge, and associated prediction uncertainty?

1.5 Scope and Limitations

This thesis focuses on the evaluation of a route-based predictive range estimator for battery electric heavy vehicles using TruckMaker simulations and MATLAB-based post-processing. The study is limited to a single vehicle configuration and a predefined route between the Port of Gothenburg and Viared. Consequently, the results should not be considered universally applicable to all vehicle types, routes, or operating conditions.

The predictive energy estimator was evaluated using simulation data rather than measurements from a physical vehicle. Although TruckMaker provides a high-fidelity

simulation environment, the obtained results may differ from real-world operation due to factors that are difficult to model accurately.

Furthermore, the study only considers traction-related battery energy consumption. Auxiliary loads such as cabin climate control, lighting, displays, battery thermal management, and other electrical systems were not included in either the predictive energy estimator or the post-processing calculations. As a result, the influence of prolonged trip duration, particularly during traffic congestion, may be underestimated.

The traffic congestion scenarios were represented by reduced speed limits along selected road segments. Real traffic queues typically involve stop-and-go driving with repeated acceleration and braking events, which were not explicitly modelled in this work. Therefore, the investigated traffic disturbances should be regarded as simplified representations of real-world congestion.

Finally, the objective of the thesis was to evaluate the behaviour of the predictive range estimation framework rather than to modify the underlying research estimator. Consequently, limitations associated with the existing speed generation model, energy prediction model, and uncertainty estimation methodology were accepted and analysed rather than redesigned.

2

Methods

This chapter describes the route selection, road data acquisition, preprocessing of input data, vehicle model configuration in TruckMaker, and implementation of a simulation environment for predictive range estimation of electric vehicles.

2.1 Overall Workflow

The overall workflow used in this thesis is presented in Figure 2.1. The methodology started with route definition and road data acquisition using HERE HD Live Map¹ integrated with TruckMaker. The collected route, weather, and mission data were converted into CSV-based input files and subsequently preprocessed using Python scripts.

The processed input data were supplied to the predictive energy estimator, which constitutes the main test object within the developed evaluation environment. In parallel, TruckMaker was used to generate a simulated vehicle response that served as the reference for evaluation. The estimator outputs, including expected energy demand and its associated uncertainty, were then post-processed and compared with the TruckMaker reference.

The main stages shown in Figure 2.1 are described in greater detail in the following sections.

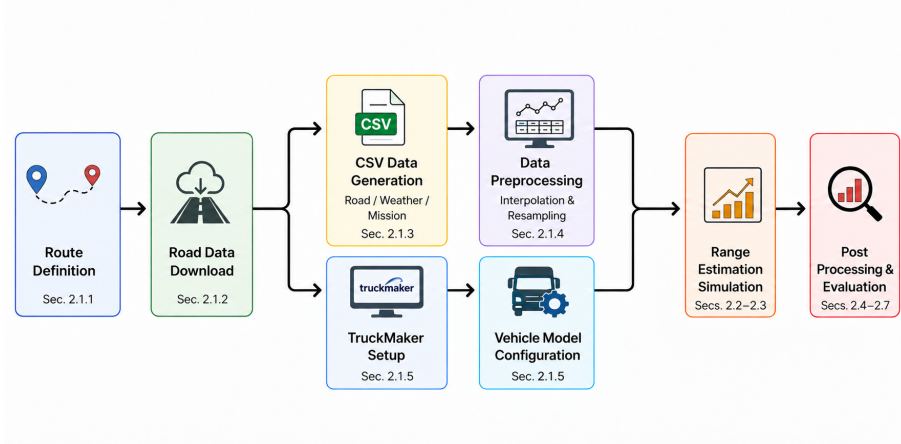


Figure 2.1: Overall workflow of the simulation and range estimation framework.

¹HERE HD Live Map, HERE Technologies. <https://www.here.com/>

2.1.1 Route Definition

A route was chosen after discussing with the supervisor and examiner. The hope was that we could run the predictive range estimator in a real truck together with the REVERE lab; the route needed to be close to Gothenburg city. Also, routes in TruckMaker can not be too long because of the computational complexity required for very long routes. Based on these considerations, a route from Skandiahamnen in Gothenburg (Skagerack 10) to Viared (Viaredsvägen) was selected, as shown in Figure 2.2. The route represents a realistic and frequently used transport route

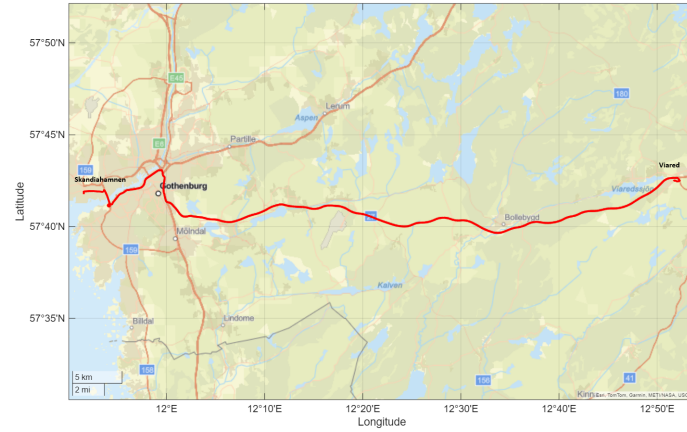


Figure 2.2: Chosen Route from Skandiahamnen to Viared

between a major port and a distribution centre. The route includes varying driving conditions, such as urban driving and highway driving with elevation changes (see Figure 2.3), roundabouts, and traffic signals. This contributes to a suitable route for analysing the vehicle's energy consumption. The route is 71 km long and takes about 50 minutes to drive with a truck.

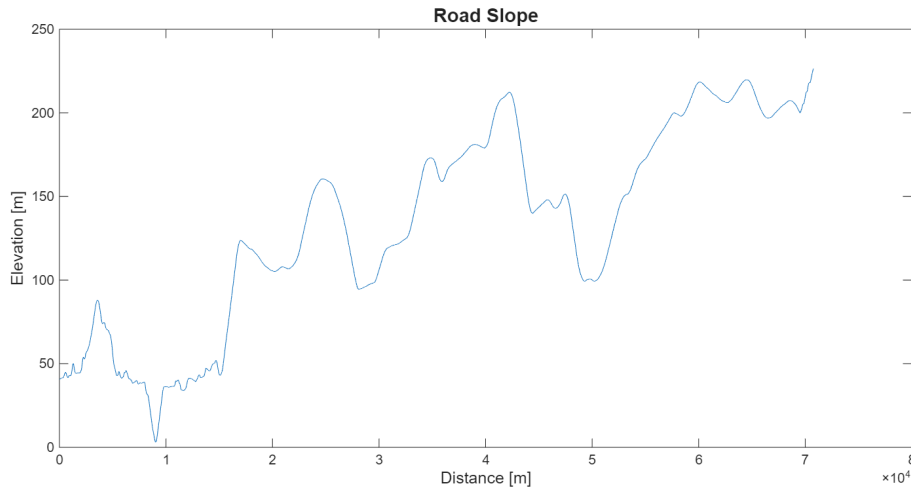


Figure 2.3: Elevation profile for chosen route

2.1.2 Downloading Data

Road data for the selected route were obtained using the HERE HD Live Map interface in TruckMaker. TruckMaker allows road data to be imported either for a defined geographical area or along a specified route. Since this study focuses on one predefined transport route, the route-based import method was used.

The route was first created in Google My Maps² and exported as a Keyhole Markup Language (KML) file containing the route coordinates. The KML file was then used as input for the HERE road data import in TruckMaker. During the import process, a small number of road connectivity issues were identified. These sections were manually corrected in TruckMaker by removing the affected road segments and reconnecting them using point-list road segments.

The resulting route data were exported for use by the predictive energy estimator. The main road-related variables included in the dataset are summarised in Table 2.1.

Table 2.1: Structure of the road data file.

Column	Unit / Format	Description
Distance	m	Travelled distance along the route
Latitude	degrees	Geographic latitude coordinate
Longitude	degrees	Geographic longitude coordinate
SpeedLimit	m/s	Posted speed limit along the route
Elevation	m	Road elevation above sea level
Slopes	degrees	Road slope or grade along the route
Curvatures	1/m	Road curvature along the route
Headings	degrees	Vehicle heading relative to north
TrafficSignals	Boolean	Indicates locations of traffic signals
StopSign	Boolean	Indicates locations of stop signs
YieldSign	Boolean	Indicates locations of yield signs
PedestrianCrossing	Boolean	Indicates locations of pedestrian crossings

2.1.3 CSV Data Generation

The predictive energy estimator requires several input datasets describing the route, environmental conditions, and transport mission. Therefore, the collected road data and the additional mission-specific information were organised into CSV files before being processed by the estimator.

Four CSV-based input files were prepared: road data, weather data, mission data, and a log file. The road data describe the characteristics of the selected route, including position, speed limits, elevation, slope, curvature, and traffic-related information. The weather file contains environmental conditions such as ambient temperature, wind speed, and wind direction, while the mission file contains mission-specific information including gross combination weight (GCW), trailer connection, and planned

²Google My Maps, Google LLC. <https://www.google.com/maps/d/>

stops. A log file is also required by the estimator framework. Since no measured vehicle log data were available or required for the scope of this study, the corresponding entries were assigned predefined neutral values.

In addition to the road data, the predictive energy estimator requires weather, mission, and vehicle log data as input. Since measured datasets for these inputs were not available within the scope of this study, representative input files were generated to match the format required by the estimator.

The weather dataset was generated in MATLAB and contained ambient temperature, wind speed, and wind direction. The estimator expects weather information for each 25 m distance point along the route and for each hour of the day. Therefore, 24 weather entries were generated for every resampled route position. The structure of the weather dataset is shown in Table 2.2.

Table 2.2: Structure of the weather data file.

Column	Unit	Description
Time	h	Timestamp of the weather
Temperature	°C	Ambient air temperature
WindSpeed	m/s	Wind speed
WindDirection	degrees	Wind direction relative to north

The mission dataset was generated separately and contains information describing the transport mission along the route. This includes trailer connection status, planned mission stops, and gross combination weight (GCW). These parameters allow the estimator to account for mission-specific operating conditions. The structure of the mission dataset is shown in Table 2.3.

Table 2.3: Structure of the mission data file.

Column	Unit / Format	Description
Distance	m	Travelled distance along the route
TrailerConnected	Boolean	Indicates whether a trailer is connected to the vehicle
MissionStop	Boolean	Indicates mission stop events along the route
GCW	kg	Gross combination weight of the vehicle configuration

In the present study, only the distance and gross combination weight (GCW) variables were actively used from the mission dataset, while the remaining fields were retained to match the input format required by the estimator.

2.1.4 Distance-Based Resampling

The road data obtained from HERE are not sampled at uniform distances along the route. Instead, the spacing between consecutive data points varied depending on

the available road geometry and map information. However, the predictive energy estimator is implemented using a fixed spatial discretisation of 25 m, and several input structures and calculations within the estimator rely on this distance interval. The raw road data therefore had to be converted to the same spatial resolution before being used by the estimator.

A common distance grid also ensures that route-related variables such as elevation, slope, curvature, speed limits, and traffic events correspond to consistent positions along the route. This allows the different input datasets to be combined and processed consistently by the estimator.

The road data were therefore resampled at fixed 25 m intervals using a Python preprocessing script, provided in Appendix 1. Numerical variables were linearly interpolated between the original data points, while Boolean event variables, such as traffic signals and stop signs, were assigned to the nearest resampled distance point. The resulting dataset therefore satisfies the spatial resolution required by the predictive energy estimator.

2.1.5 Test Vehicle

The test vehicle used in this study was based on a Volvo FH Electric 6x4 tractor configuration. Vehicle specifications were obtained from reference data in an existing heavy truck example model available within the TruckMaker simulation environment.

The selected vehicle parameters were used both in the TruckMaker simulation model and as input variables in the preprocessing and scripts developed during the project. Key parameters such as vehicle mass, drivetrain configuration, axle loads, and battery capacity were therefore consistently used throughout the complete simulation and analysis workflow. Table 2.4 presents the main vehicle parameters used in this study.

Several vehicle parameters used in the TruckMaker model were based on an existing heavy truck example model available within the TruckMaker simulation environment. Since a complete parameter set for the specific vehicle configuration was not available, representative parameters from similar truck models were used for this study. The models were considered sufficiently similar in terms of vehicle category, axle configuration, and operating characteristics. Parameters such as chassis properties, suspension characteristics, and drivetrain-related settings were therefore reused to reduce model development complexity while maintaining realistic vehicle behaviour.

The original vehicle configuration consisted of three electric motors. To simplify the implementation in TruckMaker and reduce model complexity, the propulsion system was represented by a single equivalent electric motor. The equivalent motor was configured to represent the combined power and torque characteristics of the original multi-motor configuration. This simplification reduced computational complexity while maintaining the overall longitudinal vehicle performance relevant for the scope of this study. The focus of the thesis was route-based vehicle behaviour rather than detailed powertrain dynamics.

The tractor mass was estimated to be 19 tonnes and used as an input parameter in

Table 2.4: Main vehicle parameters used in TruckMaker.

Parameter	Value	Description
Vehicle configuration	6x4 Tractor	Three axles with two driven rear axles
Motor power	500 kW	Equivalent electric propulsion system power
Motor torque	2400 Nm	Combined equivalent motor torque
Number of motors	1 equivalent motor	Simplified representation in TruckMaker
Battery capacity	540 kWh	Total installed nominal battery energy
Wheelbase	3900 mm	Distance between axle groups
Vehicle width	2550 mm	Total vehicle width
Maximum vehicle height	4.2 m	Maximum vehicle height
Front axle load	10 tonnes	Maximum front axle load
Rear axle load	23 tonnes	Bogie rear axle load
Rear axle ratio	2.83	Final drive ratio
Front tyre dimension	385/55R22.5	Front axle tyre size
Rear tyre dimension	315/70R22.5	Rear axle tyre size
Speed limiter	90 km/h	Maximum vehicle speed setting
Transmission	12-speed gear-box	Electric propulsion transmission
Tractor mass	19000 kg	Estimated tractor mass
Motor efficiency	0.95	Assumed drivetrain efficiency for the equivalent electric motor

both models. Since no exact measured mass was available, this value was selected as a reasonable approximation for the vehicle configuration. The motor efficiency was assumed to be 0.95 for the equivalent electric motor representation. These values were treated as model assumptions and are therefore included as sources of uncertainty in the results.

2.2 Energy Estimation

The predictive energy estimator used in this study was developed by Emvin et al. as part of ongoing research at Chalmers University of Technology on predictive energy estimation for road vehicles [7]. The estimator is based on a Kalman-smoother framework for known-route energy demand prediction. Only the aspects of the framework relevant to the implementation and evaluation performed in this thesis are described in this section.

It is based on a Kalman-filter-based framework for predictive energy demand estimation. The implementation combines multiple input sources, including road data,

weather conditions, mission-specific parameters, and vehicle properties, to estimate expected propulsion energy demand and regenerative braking, along with their associated uncertainty, along a predefined route. Figure 2.4 presents the overall estimator architecture used in this project. The framework utilises route-related information such as speed limits, traffic signals, road topology, and environmental conditions, together with mission-specific inputs including gross combination weight (GCW), trailer configuration, and route definition. These inputs are processed through a sequence of estimation stages.

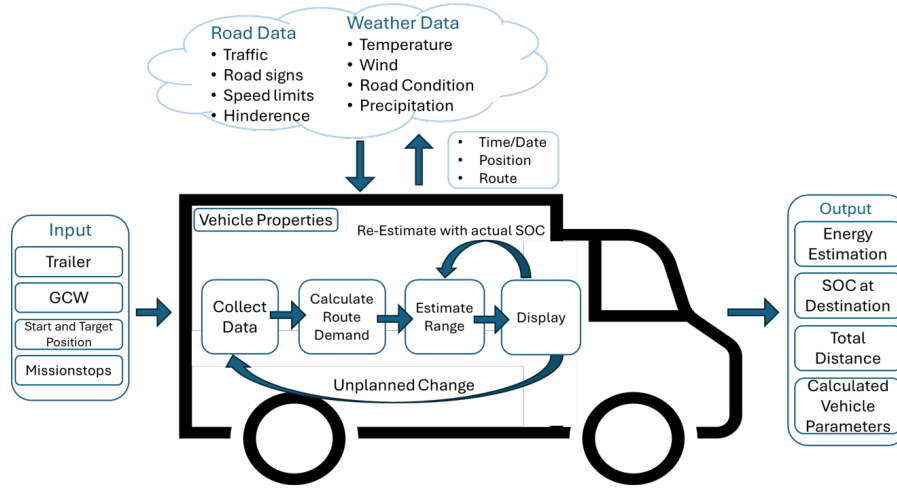


Figure 2.4: Estimator workflow

The estimator implementation consists of a main script together with a dedicated function library containing the relevant estimation functions. The framework includes motion models, measurement models, Kalman prediction and update steps, backwards-pass estimation, and uncertainty handling. Sigma-point-based estimation methods are also included in order to handle nonlinear system behaviour within the vehicle and energy demand calculations.

The tyre behaviour used in the estimator was based on the tyre modelling work presented by Hyttinen [12]. The tyre model was integrated as part of the longitudinal vehicle dynamics and energy demand calculations.

The outputs from the estimator include predicted energy consumption with uncertainty, route distance information, and estimated vehicle-related parameters.

2.3 Energy-to-Range Conversion

The predictive energy estimator described in Section 2.2 provides the accumulated expected battery energy consumption along the route. Since the objective of this thesis is to evaluate vehicle state of charge (SOC), remaining driving range, and predicted destination SOC, the estimator output was further processed in MATLAB to convert the predicted energy demand into vehicle-level performance metrics.

The accumulated battery energy consumption at a travelled distance s is denoted by $E_{b,cons}(s)$. Assuming a known initial state of charge, SOC_{init} , and a total battery energy capacity, $E_{b,tot}$, the estimated SOC was calculated as

$$SOC = SOC_{init} - \frac{E_{b,cons}(s)}{E_{b,tot}}. \quad (2.1)$$

Here, SOC is expressed as a fraction of the total battery capacity.

Since the battery was not assumed to be usable down to zero SOC, a minimum allowable state of charge, SOC_{min} , was introduced. The remaining usable battery energy at position s was therefore calculated as

$$E_{b,rem,usable}(s) = (SOC(s) - SOC_{min}) E_{b,tot}. \quad (2.2)$$

To estimate the remaining driving range, the specific energy consumption (SEC) was calculated from the predicted battery energy consumption and the corresponding travelled distance. The SEC is expressed in kWh/km. The remaining range was then estimated according to

$$Range_{rem}(s) = \frac{E_{b,rem,usable}(s)}{SEC(s)}. \quad (2.3)$$

This calculation assumes that the predicted specific energy consumption is representative of the subsequent driving conditions.

Since the selected route between Skandiahammen and Viared is shorter than the expected maximum driving range of the vehicle, the complete reachable distance cannot be determined directly from the simulated route. The accumulated energy consumption curve was therefore extrapolated in MATLAB until the predicted SOC reached the predefined minimum value SOC_{min} . The corresponding travelled distance was defined as the predicted total driving range.

In addition to current SOC and remaining range, the expected SOC at the destination was calculated continuously along the route. At each position s , the predicted energy required to travel from the current position to the destination was determined from the estimator output as

$$E_{b,dest}(s) = E_{b,cons}(s_{dest}) - E_{b,cons}(s), \quad (2.4)$$

where s_{dest} denotes the route distance at the destination. The predicted destination SOC was then calculated as

$$SOC_{dest}(s) = SOC(s) - \frac{E_{b,dest}(s)}{E_{b,tot}}. \quad (2.5)$$

The uncertainty bounds provided by the energy estimator were converted to corresponding SOC bounds using the same energy-to-SOC relationship. This made it possible to evaluate both the expected SOC prediction and its associated prediction uncertainty throughout the route.

The resulting MATLAB post-processing workflow is summarised in Figure 2.5. The calculated quantities, including current SOC, predicted destination SOC, remaining range, and total predicted range, were subsequently compared with the TruckMaker

reference and used in the re-estimation and sensitivity analyses presented later in this thesis.

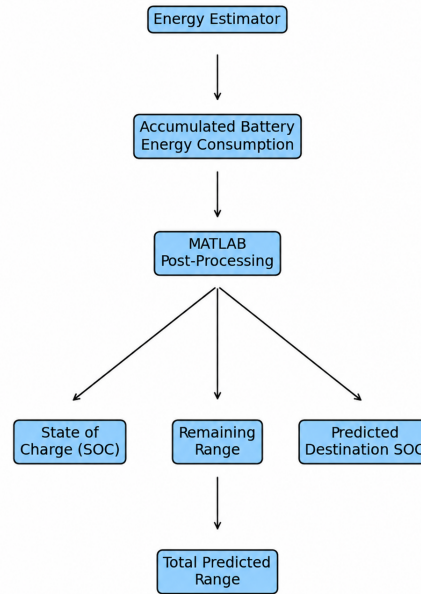


Figure 2.5: Post-processing workflow used to convert accumulated battery energy consumption into vehicle-level performance metrics.

2.4 Post Processing

The simulation outputs generated from the TruckMaker environment and the predictive energy estimator, together with the complementary MATLAB script, were post-processed for evaluation and visualisation purposes. Relevant output signals such as predicted energy consumption, estimated state of charge, vehicle speed profile, route position, and estimated driving range were analysed using MATLAB-based scripts.

The post-processing stage also included the generation of route-based plots and the comparison of estimated vehicle behaviour under different operating conditions. The processed results were used to evaluate the estimator’s performance and to support visualisation of the predictive range estimation framework.

2.5 Estimation Frequency

A route-based range estimator is typically not executed only once at the beginning of a trip. Instead, the prediction is continuously updated as new vehicle information becomes available. To investigate the influence of update frequency on prediction accuracy, a re-estimation strategy was implemented in the post-processing stage.

The principle of the re-estimation process is illustrated in Figure 2.6. An initial prediction of the state of charge (SoC) at the destination is generated before the vehicle starts the mission. As the vehicle progresses, the actual SoC from the TruckMaker simulation is used to update the estimator at predefined distances. At each update point, the current vehicle state replaces the previous estimate, and the remaining route is re-evaluated using the predictive energy estimator. Several distance-based update frequencies were evaluated.

The predicted destination SoC obtained from each re-estimation was compared with the reference value from the TruckMaker simulation. This approach made it possible to analyse how frequently the estimator must be updated in order to maintain an accurate prediction throughout the route.

In addition to the destination SoC prediction, the prediction error was evaluated as a function of travelled distance. This allowed the convergence behaviour of the estimator to be analysed and provided insight into the relationship between update frequency and estimation accuracy.

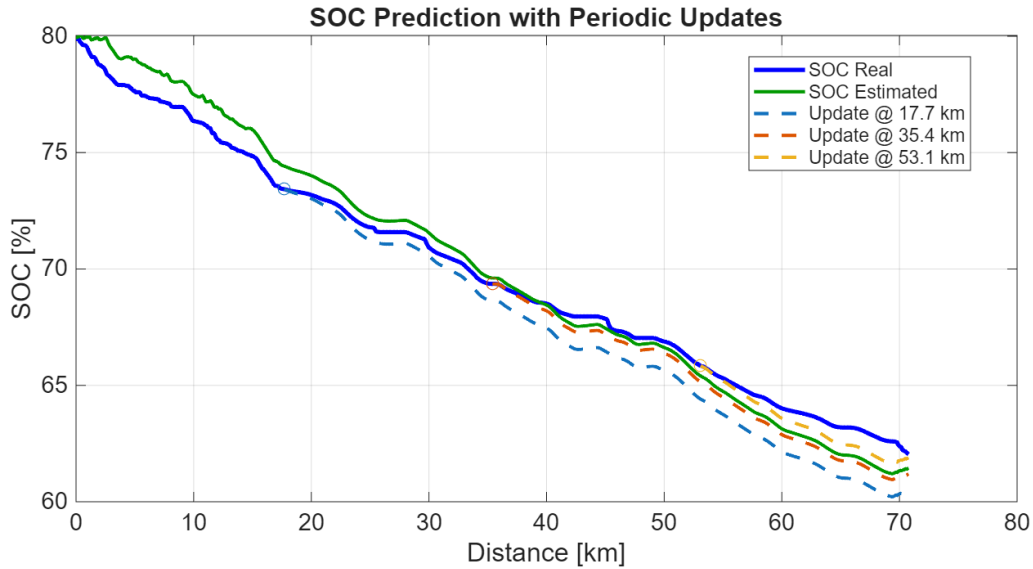


Figure 2.6: Example of periodic re-estimation during the route.

2.6 Unplanned Events During Route

In real-world transport operations, the conditions assumed at the start of a trip may change during the journey. To evaluate the robustness of the predictive range estimator, some unplanned events were introduced, see table 2.6. The purpose was to investigate how quickly and accurately the estimator could adapt when important assumptions no longer matched the actual operating conditions.

The first disturbance scenario investigated the effect of incorrect vehicle mass information. Two separate cases were evaluated. In the first case, the predictive energy estimator was provided with an incorrect gross combination weight (GCW) of 23 tonnes throughout the entire route, while the reference case used a GCW of

Table 2.6: Unplanned event scenarios used for estimator evaluation.

Scenario	Modification	Purpose
Incorrect vehicle mass	GCW set to 23 t during the entire route	Evaluate the prediction error caused by an incorrect vehicle mass assumption.
Mass correction	GCW initially set to 23 t and corrected to 19 t at 35.4 km	Evaluate the estimator's ability to recover from incorrect vehicle mass information through re-estimation.
Unknown traffic disturbance	Speed limit reduced to 2.77 m/s between 39.4 km and 45.2 km, but not included in the initial prediction	Evaluate the estimator's response to unforeseen traffic conditions.
Known traffic disturbance	Speed limit reduced to 10 km/h between 39.4 km and 45.2 km and included in the initial prediction	Evaluate the benefit of traffic information available from external data sources such as HERE.

19 tonnes. This scenario was used to quantify the prediction error caused by an incorrect vehicle mass assumption.

In the second case, the route was initially evaluated using the same incorrect GCW of 23 tonnes. However, at the second re-estimation point, located approximately halfway through the route (35.4 km), the vehicle mass information was corrected to the actual value of 19 tonnes. This scenario involves incorrect payload information entered before departure, later corrected during operation. By comparing the corrected and uncorrected cases, it was possible to evaluate how effectively the re-estimation process could compensate for incorrect input parameters during an ongoing trip.

The second disturbance scenario investigated the effect of unexpected traffic conditions. A traffic congestion event was introduced by reducing the speed limit in the road input data to 10 km/h between 39.4 km and 45.2 km along the route, representing a traffic queue caused by an accident.

Two separate cases were evaluated. In the first case, the predictive energy estimator generated its initial prediction using the original route data without any information about the traffic disturbance. The vehicle was then exposed to the low-speed section during the simulation, causing a mismatch between the predicted and actual driving conditions. This scenario was used to evaluate how the estimator adapted to unforeseen traffic events through the re-estimation process.

In the second case, the traffic disturbance was included in the route data before the initial prediction was generated. This represents a situation where real-time traffic information from external sources, such as HERE traffic services, is available before starting. The purpose was to investigate how access to traffic information affects prediction accuracy and to compare the resulting estimates with those obtained when the disturbance was initially unknown.

By comparing the two cases, the influence of traffic information availability on pre-

diction accuracy and estimator robustness could be assessed. For both scenarios, the resulting changes in predicted energy consumption, state of charge at destination, and prediction error were analysed. The scenarios were compared with the reference case in order to assess the estimator's ability to adapt to changing operating conditions and improve prediction accuracy through re-estimation.

2.7 Driver Parameter Identification and Sensitivity Analysis

To investigate whether previously observed vehicle behaviour could be used to adapt the predictive estimator, two driver-related parameters, K and $\sigma_{v,\text{ref}}$, were identified using data from the first half of the route.

The driver model relates the longitudinal force demand to the difference between the reference speed and the actual vehicle speed according to

$$F_t = K (v_{\text{ref,comp}} - v_{\text{real}}), \quad (2.6)$$

where K is the proportional driver response parameter, F_t is the total longitudinal force, v_{real} is the actual vehicle speed, and $v_{\text{ref,comp}}$ is a compensated reference speed. The reference-speed signal originates from the deterministic strategic-driver model, which represents the route-dependent speed behaviour of the driver.

For the parameter identification, the reference speed v_{ref} was obtained from the predictive estimator, while v_{real} and F_t were obtained from the TruckMaker simulation. Since the TruckMaker signals and the estimator output were sampled at different distance points, duplicate TruckMaker distance values were first removed. The TruckMaker speed and longitudinal force were subsequently linearly interpolated onto the distance grid used by the predictive estimator.

The speed difference at each distance point was calculated as

$$\Delta v_i = v_{\text{ref},i} - v_{\text{real},i}. \quad (2.7)$$

The mean speed difference was then calculated according to

$$\overline{\Delta v} = \frac{1}{N} \sum_{i=1}^N \Delta v_i, \quad (2.8)$$

where N is the number of samples.

The reference-speed uncertainty was estimated from the variation in the speed difference around its mean value as

$$\sigma_{v,\text{ref}} = \sqrt{\frac{1}{N} \sum_{i=1}^N (\Delta v_i - \overline{\Delta v})^2}. \quad (2.9)$$

To remove the mean offset between the reference and simulated speed profiles, the reference speed was compensated according to

$$v_{\text{ref,comp},i} = v_{\text{ref},i} - \overline{\Delta v}. \quad (2.10)$$

For the identification of K , the compensated speed difference was collected in the vector

$$\Delta \mathbf{v}_{\text{comp}} = \mathbf{v}_{\text{ref,comp}} - \mathbf{v}_{\text{real}}. \quad (2.11)$$

Here, $\Delta \mathbf{v}_{\text{comp}}$ and $\mathbf{F}_t$ are $N \times 1$ vectors containing the compensated speed differences and corresponding longitudinal force values, respectively. The proportional driver model can then be written in vector form as

$$\mathbf{F}_t = \Delta \mathbf{v}_{\text{comp}} K. \quad (2.12)$$

The least-squares estimate of K was obtained using the Moore–Penrose pseudoinverse,

$$K = \Delta \mathbf{v}_{\text{comp}}^\dagger \mathbf{F}_t. \quad (2.13)$$

After identifying K and $\sigma_{v,\text{ref}}$, sensitivity analyses were performed to investigate their influence on the predicted energy consumption and prediction uncertainty. Each parameter was varied individually while the remaining estimator inputs were kept unchanged.

For each simulation, the mean predicted energy consumption and the corresponding energy uncertainty were evaluated. The energy uncertainty was obtained from the upper and lower energy bounds provided by the estimator and was defined as

$$U_E = \frac{E_{\text{upper}} - E_{\text{lower}}}{2}. \quad (2.14)$$

Finally, the values of K and $\sigma_{v,\text{ref}}$ identified from the first half of the route were individually applied to the second half of the route. At the midpoint, the SOC prediction was re-initialised using the corresponding TruckMaker SOC. The resulting predictions were compared with both the original estimator configuration and the TruckMaker reference.

3

Results

This chapter presents the results obtained from the predictive range estimation framework developed in this thesis. The performance of the energy estimator is evaluated using both TruckMaker simulation data and MATLAB-based post-processing. The results are organised into five main parts. First, the reference case is presented to provide a baseline comparison between the energy estimator and the TruckMaker simulation. Second, the influence of re-estimation frequency is investigated by analysing how different update intervals affect prediction accuracy throughout the route. Third, the impact of incorrect vehicle mass information and mid-route mass correction is evaluated. The influence of unexpected traffic disturbances and the availability of traffic information is analysed. Finally, the driver-related parameters K and $\sigma_{v,\text{ref}}$ are identified, and their influence on energy consumption, uncertainty, and SOC is investigated.

The presented results focus on state of charge (SOC), predicted destination SOC, prediction error, and estimated driving range. Together, these metrics provide a basis for evaluating the accuracy, robustness, and practical applicability of the predictive range estimation approach.

3.1 Reference Case

The reference case was used as the baseline scenario throughout this study and represents the nominal operating conditions assumed by both the predictive energy estimator and the TruckMaker simulation. The route between Skandiahamnen and Viared was simulated using the vehicle parameters presented in Chapter 2.1.5, together with the corresponding route, weather, and mission data.

The purpose of the reference case was to evaluate the estimator's performance under consistent operating conditions and to establish a benchmark for comparison with the disturbance scenarios presented later in this chapter. The results presented in this section include comparisons between simulated and estimated vehicle behaviour, focusing on vehicle speed, state of charge (SOC), and predicted destination SOC.

3.1.1 Vehicle Speed Profile

Figure 3.1 compares the vehicle speed profile generated by the predictive energy estimator with the corresponding speed profile obtained from the TruckMaker simulation. The comparison was performed along the entire route between Skandiahamnen and Viared.

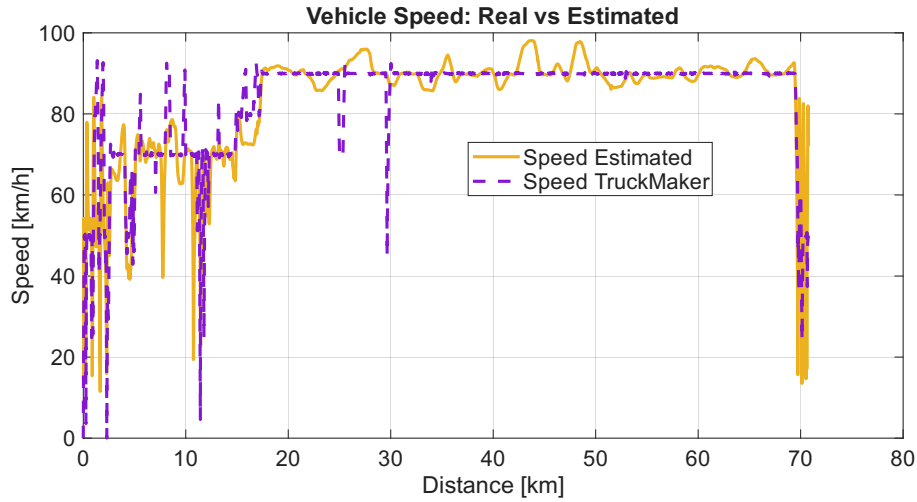


Figure 3.1: Predicted Speed Profile and TruckMaker Speed Profile

Overall, the estimated speed profile follows the simulated vehicle speed reasonably well throughout the route. The largest deviations occur during the first kilometres of the route, where several intersections, traffic signals, and speed transitions are present. In these sections, the estimator predicts more frequent speed variations than those observed in the TruckMaker simulation. Similar differences can also be observed near the end of the route, where the vehicle approaches its destination.

Two sharp speed drops at 25 and 30 km can be observed in the TruckMaker speed profile during highway driving. These events are not consistently reflected in the estimated speed profile and may originate from imperfections in the route generated from the HERE road data. During the route generation process, a number of issues related to road connectivity and imported road segments were identified and manually corrected.

For the majority of the highway section, approximately between 18 km and 68 km, both profiles remain close to the speed limit of 90 km/h and show good agreement. Minor deviations can be observed due to differences in how the estimator and the TruckMaker driver model handle acceleration and road geometry.

The results indicate that the speed generation model captures the overall driving behaviour of the route and provides a reasonable basis for subsequent energy consumption estimation. Since vehicle speed is one of the most influential factors affecting energy demand, a realistic speed profile is essential for obtaining accurate range predictions.

3.1.2 State of Charge

The state of charge (SOC) estimated by the predictive energy estimator was compared with the corresponding SOC obtained from the TruckMaker simulation. Figure 3.2 presents the SOC evolution along the complete route.

Overall, the estimated SOC follows the simulated SOC closely throughout the route. Both curves show a continuous decrease from approximately 80% at the start of the route to approximately 62% at the destination. The agreement between the curves

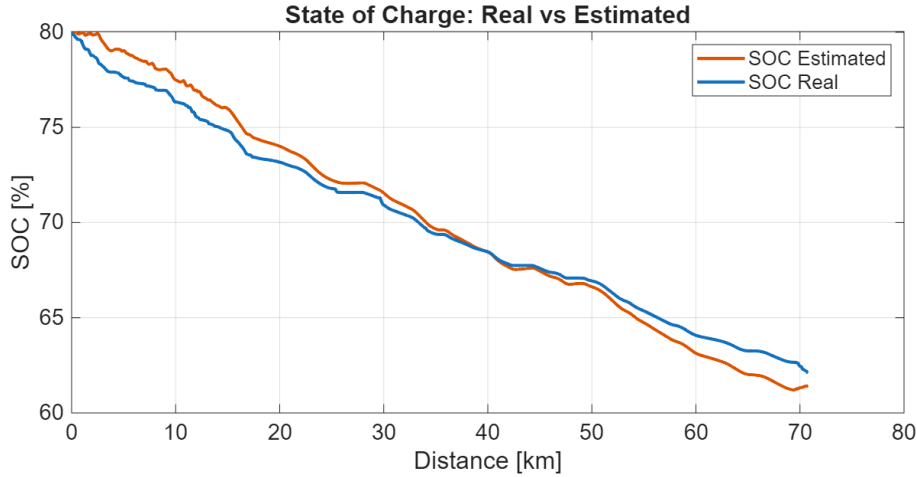


Figure 3.2: State of Charge: TruckMaker vs Predicted

indicates that the estimator captures the overall energy consumption behaviour of the vehicle with good accuracy.

A noticeable difference is that the estimated SOC curve exhibits a slightly steeper gradient than the TruckMaker reference. During the first part of the route, the estimated SOC remains somewhat higher than the simulated SOC, indicating a lower predicted energy consumption. As the vehicle progresses along the route, the difference gradually decreases, and the two curves intersect around the middle of the route. Beyond this point, the estimator predicts a slightly faster depletion of battery energy, causing the estimated SOC to fall below the TruckMaker reference towards the end of the route.

This behaviour suggests that the estimator slightly overestimates the total energy consumption over the complete route. However, the deviation remains relatively small, and the overall trend is captured well throughout the simulation.

To further investigate local differences between the estimated and simulated energy consumption, the rate of change of SOC with respect to distance was compared. Figure 3.3 shows the difference between the estimated and simulated SOC gradients. The SOC rate error remains close to zero over large parts of the route, indicating similar local energy consumption between the estimator and the TruckMaker reference. Larger deviations occur mainly during the first part of the route and near the destination, where the vehicle encounters more frequent changes in speed and operating conditions. This is consistent with the differences observed in the corresponding vehicle speed profiles.

Figure 3.4 presents the estimated SOC together with the uncertainty bounds generated by the estimator. The shaded region represents the estimated confidence interval, while the upper and lower bounds indicate the expected variation in the prediction.

In addition to the mean accumulated battery energy consumption estimate, denoted by $E_{batt,s}$, the estimator also provides an estimate of the corresponding standard deviation, σ_e . The uncertainty bounds are calculated directly within the estimator according to

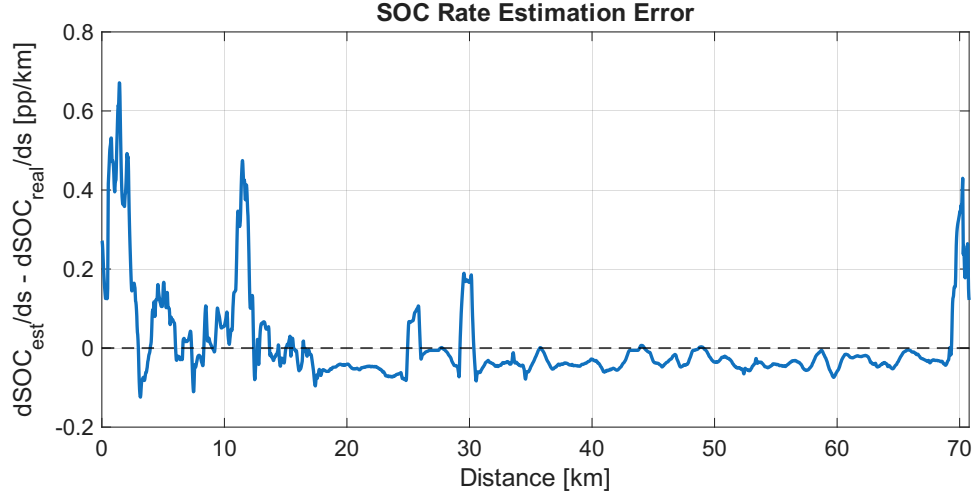


Figure 3.3: Difference between the estimated and simulated SOC rate with respect to travelled distance for the reference case.

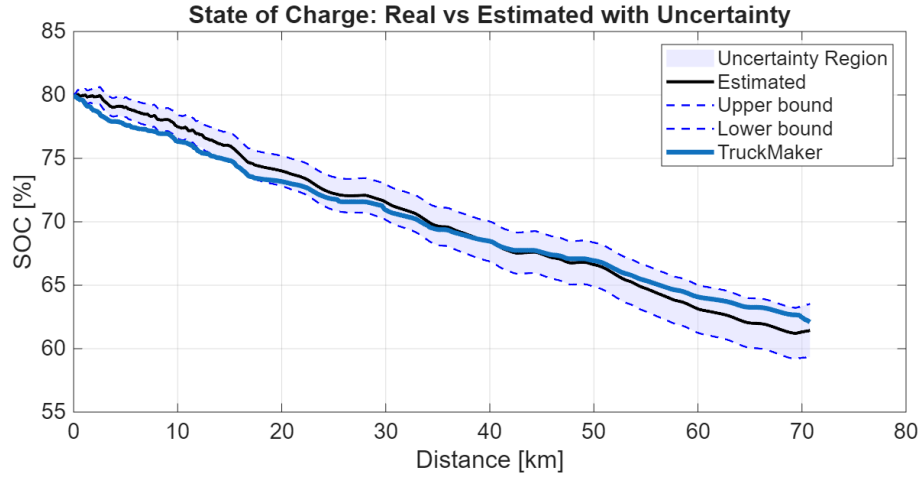


Figure 3.4: State of Charge: TruckMaker vs Predicted with Uncertainty

$$E_{upper} = E_{batt,s} + 3\sigma_e \quad (3.1)$$

$$E_{lower} = E_{batt,s} - 3\sigma_e \quad (3.2)$$

where E_{upper} and E_{lower} represent the upper and lower battery energy consumption bounds, respectively. The resulting interval corresponds to a $\pm 3\sigma$ confidence region around the mean estimate. Assuming an approximately Gaussian distribution of the prediction error, this interval contains 99.7% of all possible outcomes.

The battery energy uncertainty was propagated through the MATLAB post-processing calculations using the same methodology as for the nominal energy estimate. Consequently, the upper and lower SOC bounds shown in Figure 3.4 originate from the same accumulated battery energy consumption estimate, $E_{batt,s}$, that is used to calculate the nominal SOC prediction.

The TruckMaker reference SOC almost remains within the uncertainty bounds throughout the entire route. This indicates that the uncertainty estimation captures the observed prediction error and provides a realistic representation of the estimator's confidence. Although the estimated SOC does not perfectly match the reference simulation at every point, the actual vehicle behaviour remains within the predicted uncertainty interval.

The uncertainty region gradually increases along the route, reflecting the accumulation of uncertainty associated with long-horizon energy predictions. This behaviour is expected, as small modelling inaccuracies and disturbances accumulate as the prediction horizon increases. The results therefore suggest that the estimator not only provides accurate SOC predictions but also produces meaningful uncertainty estimates that can be used to assess the reliability of the prediction.

3.2 Influence of Re-Estimation Frequency

The influence of re-estimation frequency was investigated by comparing SOC predictions obtained using three different distance-based update intervals: 8.75 km, 17.5 km, and 35 km. At each re-estimation point, the current SOC from the TruckMaker simulation was used to initialise a new prediction for the remaining route, as described in Section 2.5.

The results are presented in terms of the predicted SOC development along the route and the corresponding prediction error at the destination. The purpose was to evaluate how the frequency of periodic updates influences prediction accuracy and the estimator's ability to compensate for deviations between predicted and simulated vehicle behaviour.

3.2.1 SOC Prediction with Periodic Re-Estimation

Figure 3.5 illustrates the influence of periodic re-estimation on the predicted SOC throughout the route. The figure compares the original SOC prediction with the TruckMaker reference and the updated predictions generated at approximately 17.7 km, 35.4 km, and 53.1 km.

The original SOC prediction follows the TruckMaker reference reasonably well, as previously observed in Section 3.1.2. Consequently, the estimator gradually transitions from overestimating the remaining SOC during the first part of the route to being more accurate towards the destination.

At each re-estimation point, the predicted SOC is re-initialised using the corresponding SOC from TruckMaker. This corrects the accumulated difference between the estimated and simulated SOC at the update location. However, since the underlying energy consumption model remains unchanged, deviations may develop again as the vehicle continues along the remaining route.

The updated predictions show how the estimated SOC at the destination changes depending on where the re-estimation is performed. The prediction generated at 17.7 km results in a lower destination SOC than the original estimate, while the subsequent updates at 35.4 km and 53.1 km produce predictions that are closer to the TruckMaker reference.

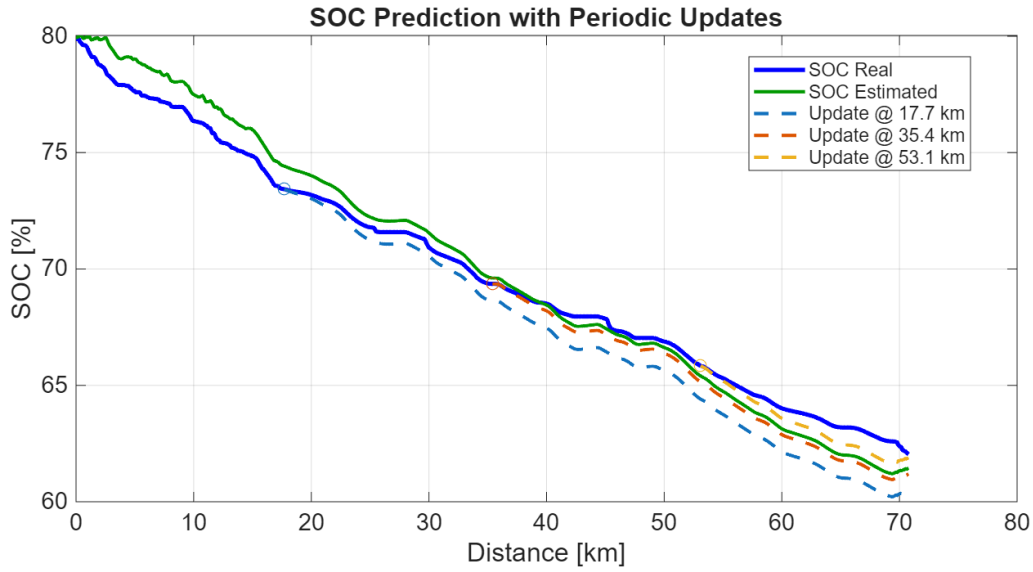


Figure 3.5: SOC predictions throughout the route.

These results demonstrate that periodic re-estimation can compensate for accumulated SOC prediction errors by incorporating the current vehicle state. However, the accuracy of each updated prediction still depends on how well the estimator represents the energy consumption over the remaining route. The influence of different re-estimation intervals on the destination SOC prediction error is examined further in Section 3.2.2.

3.2.2 Prediction Error at Destination

Figure 3.6 shows the prediction error of the estimated state of charge at the destination for three different re-estimation intervals. The prediction error is expressed in percentage points and is calculated as the difference between the predicted destination SOC and the final SOC obtained from the TruckMaker simulation.

At the start of the route, all update intervals show a negative prediction error of approximately -0.6 percentage points. This means that the estimator initially predicts a slightly lower SOC at the destination than the TruckMaker reference. As the route progresses, the prediction error changes as new re-estimations are performed using the current vehicle SOC.

The 8,75 km update interval shows the largest variation in prediction error, especially during the first part of the route. This is likely because the more frequent updates capture local differences between the estimator and the TruckMaker simulation more clearly. The 17,5 km and 35 km update intervals show a smoother error development because fewer re-estimation points are used.

Towards the end of the route, all three update intervals converge towards the zero-error line. This indicates that the prediction of destination SOC improves as the remaining route distance decreases and more information about the actual vehicle behaviour becomes available. The final errors remain within approximately ± 0.5 percentage points, which indicates good agreement between the estimator and the TruckMaker reference for the investigated route.

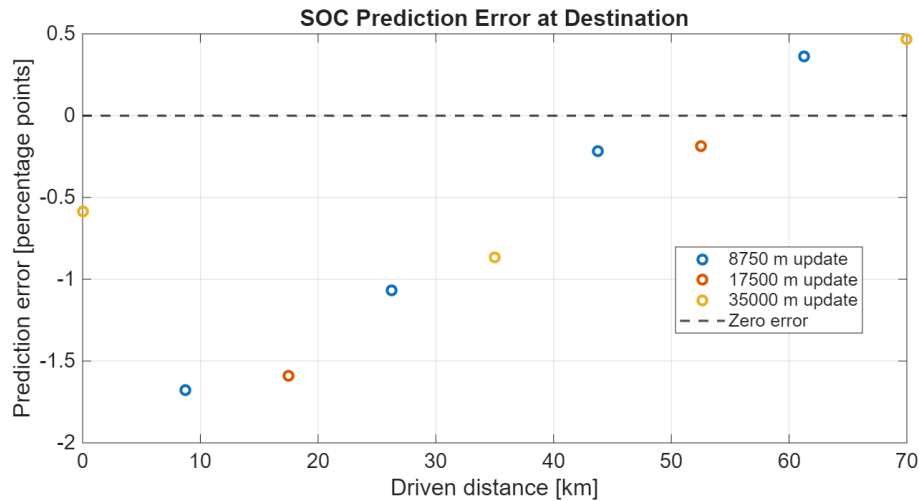


Figure 3.6: Prediction error of the estimated destination SOC for different re-estimation intervals. The dashed line represents zero error relative to the TruckMaker reference.

3.3 Influence of Vehicle Mass Input

The influence of vehicle mass information was investigated using scenarios with incorrect and subsequently corrected gross combination weight (GCW). The analysis focuses on the resulting effects on predicted SOC and driving range.

3.3.1 Incorrect Vehicle Mass

To investigate the influence of incorrect vehicle mass information, the predictive energy estimator was provided with a gross combination weight (GCW) of 23 tonnes, while the TruckMaker simulation was performed using the reference vehicle mass of 19 tonnes. No mass correction was applied during the route, meaning that the estimator relied on the incorrect vehicle mass throughout the entire journey.

Figure 3.7 shows the resulting SOC prediction together with periodic re-estimations. Since the estimator assumes a heavier vehicle, it predicts a higher energy consumption than observed in the TruckMaker simulation. Consequently, the estimated SOC decreases more rapidly than the reference SOC throughout the route. The difference becomes increasingly visible as the travelled distance increases, indicating that the prediction error accumulates when the incorrect mass assumption is maintained.

The influence of the incorrect mass assumption can be illustrated more clearly by analysing the predicted total reachable distance. To improve the visibility of the effect, the battery capacity was scaled such that the reference vehicle could only just complete the route. This increases the sensitivity of the range prediction and makes differences between the estimated and actual vehicle behaviour easier to observe.

Figure 3.8 shows that the estimator initially predicts a total reachable distance of approximately 60 km, whereas the TruckMaker reference indicates a reachable distance of approximately 71 km. The incorrect mass assumption, therefore, causes a significant underestimation of the vehicle range.

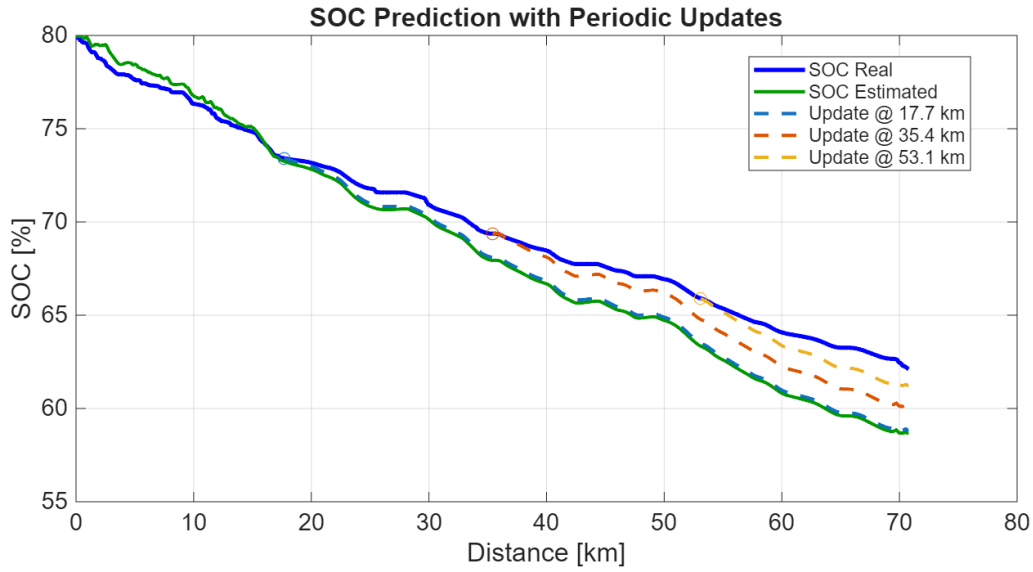


Figure 3.7: SOC prediction obtained when the estimator assumes a vehicle mass of 23 tonnes, while the TruckMaker simulation uses the reference mass of 19 tonnes.

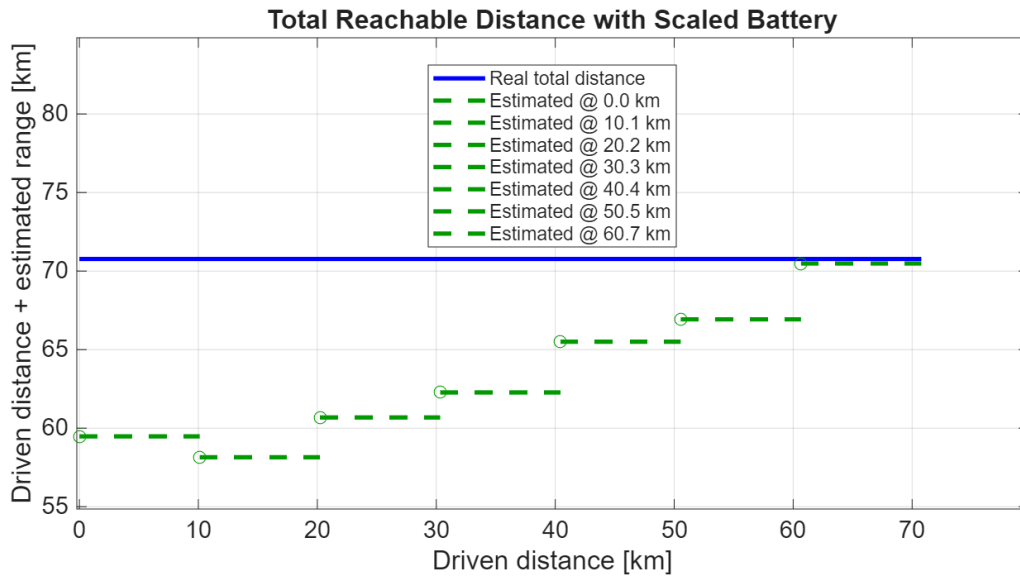


Figure 3.8: Predicted total reachable distance obtained using an incorrect vehicle mass of 23 tonnes. The battery capacity was scaled to approximately match the route length to emphasise the influence of the mass mismatch.

As additional re-estimations are performed, the predicted reachable distance gradually increases and approaches the reference value. However, because the underlying mass assumption remains incorrect, a systematic prediction error persists throughout the route.

3.3.2 Mass Correction During Route

To evaluate the ability of the predictive energy estimator to recover from incorrect vehicle information, a mass correction scenario was investigated. Similar to the previous case, the estimator initially assumed a gross combination weight (GCW) of 23 tonnes, while the TruckMaker simulation was performed using the reference vehicle mass of 19 tonnes. However, unlike the previous scenario, the correct vehicle mass was introduced at the second re-estimation point, located approximately halfway through the route at 35.4 km.

The purpose of this scenario was to represent a realistic situation in which incorrect payload information is entered before departure and later corrected during operation. By comparing the corrected and uncorrected cases, it is possible to evaluate how effectively the re-estimation process can compensate for inaccurate input parameters.

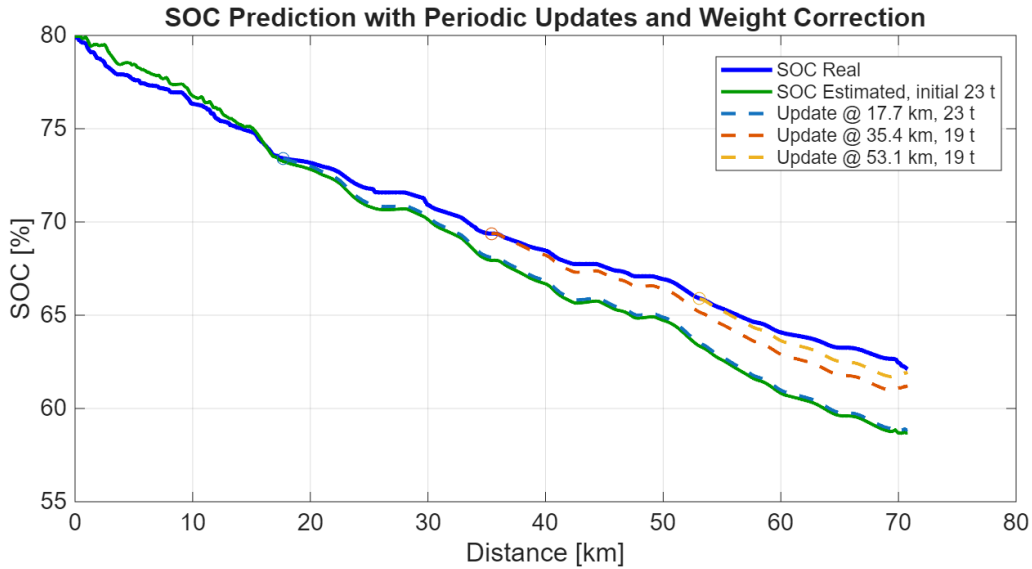


Figure 3.9: SOC prediction obtained when the estimator initially assumes a vehicle mass of 23 tonnes and the correct mass of 19 tonnes is introduced at the second re-estimation point.

Figure 3.9 shows the resulting SOC predictions throughout the route. The initial prediction and the first re-estimation are both based on the incorrect vehicle mass and therefore predict a higher energy consumption than observed in the TruckMaker simulation. Consequently, the estimated SOC decreases more rapidly than the reference SOC and the destination SOC is underestimated.

At the second re-estimation point, located at approximately 35.4 km, the correct vehicle mass is introduced to the estimator. This results in an immediate improvement of the destination SOC prediction, as the subsequent re-estimations are based on a more representative vehicle model. The updated prediction curves move noticeably closer to the TruckMaker reference compared with the scenario where the incorrect mass assumption was maintained throughout the entire route.

The improvement can be observed by comparing the predictions generated at 35.4 km and 53.1 km with the corresponding predictions obtained in the previous scenario

(Figure 3.7). After the mass correction, the estimator predicts a higher remaining SOC at the destination, indicating that the predicted energy consumption better matches the actual vehicle behaviour.

Although the correction does not eliminate the accumulated prediction error, the results demonstrate that the re-estimation process can effectively compensate for incorrect input parameters when updated information becomes available. Comparing this scenario with the case where the incorrect vehicle mass was maintained throughout the route shows that correcting the vehicle mass significantly improves the prediction accuracy and reduces the error in the estimated destination SOC.

3.4 Influence of Traffic Disturbances

The influence of traffic disturbances was investigated using two scenarios: unexpected congestion and congestion information available before departure. The analysis focuses on the effects on vehicle speed, predicted SOC, and driving range.

3.4.1 Unexpected Traffic Congestion

To evaluate the influence of unforeseen traffic events, a traffic congestion scenario was introduced along the route. The congestion was simulated by reducing the speed limit to 10 km/h between approximately 39 km and 45 km, representing a traffic queue caused by an accident. The length of the congestion was intentionally extended compared with a typical traffic queue in order to amplify its effect on vehicle energy consumption and prediction accuracy, thereby making the resulting differences easier to analyse. The predictive energy estimator generated its initial prediction using the original route data and was therefore unaware of the traffic disturbance at the start of the journey.

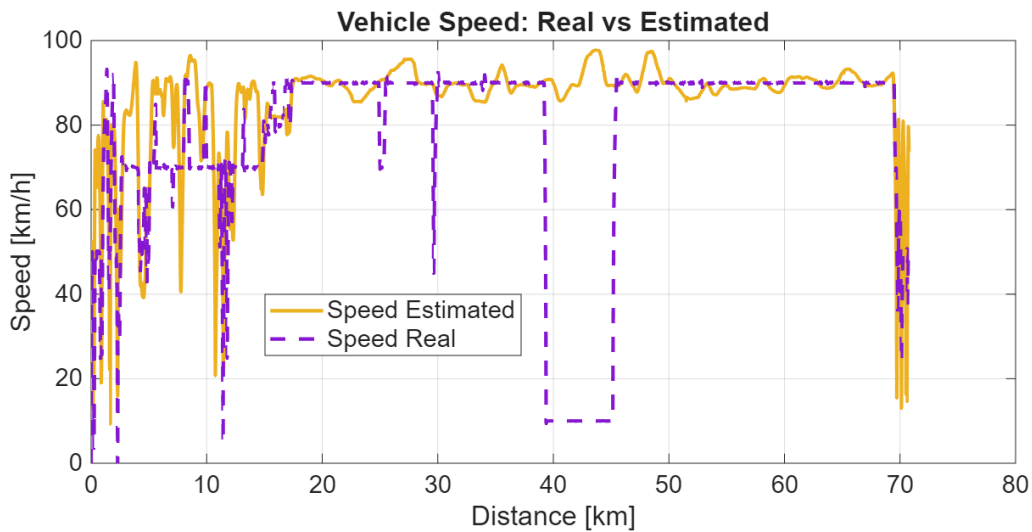


Figure 3.10: Vehicle speed profile for the traffic congestion scenario. The simulated vehicle encounters an unexpected low-speed section caused by a traffic disturbance between approximately 39 km and 45 km.

Figure 3.10 shows the resulting vehicle speed profile. A significant speed reduction can be observed between approximately 39 km and 45 km, where the vehicle speed drops to 10 km/h. Since this disturbance was not included in the initial prediction, the estimator assumes non-traffic conditions while the TruckMaker simulation experiences prolonged low-speed operation.

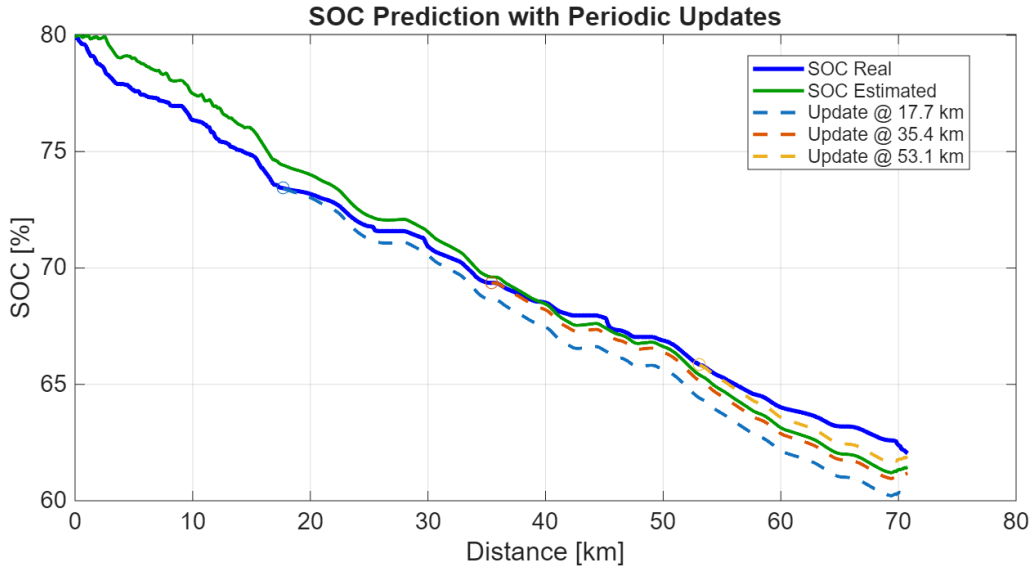


Figure 3.11: SOC prediction throughout the route for the traffic congestion scenario. The estimator is unaware of the traffic disturbance during the initial prediction and gradually adapts through periodic re-estimations.

The influence of the unexpected congestion on the predicted state of charge is shown in Figure 3.11. Before the congestion occurs, the predicted SOC follows the trajectory of the reference case. The periodic re-estimations gradually compensate for this mismatch by incorporating updated vehicle SOC. As a result, the destination SOC prediction is continuously corrected throughout the remainder of the route. Although a small prediction error remains after the traffic disturbance, the re-estimation process successfully reduces the gap between the predicted and simulated vehicle behaviour slightly.

The impact of the congestion can also be observed in Figure 3.12, which presents the predicted total reachable distance throughout the route. Similar to the vehicle mass study, the battery capacity was scaled such that the reference vehicle could approximately complete the route.

Following each re-estimation, the predicted reachable distance gradually converges towards the TruckMaker reference as updated SOC information becomes available. However, the influence of the traffic congestion on the overall prediction is relatively small. Comparing Figures 3.11 and 3.12 with the corresponding results from the reference case shows that both the SOC evolution and the predicted reachable distance remain largely unchanged despite the introduced traffic disturbance.

This suggests that the prolonged low-speed section has only a minor impact on the total energy consumption of the vehicle in the TruckMaker simulation. Consequently, the initial prediction generated before the congestion occurs remains reasonably accurate throughout the route. The re-estimation process still improves

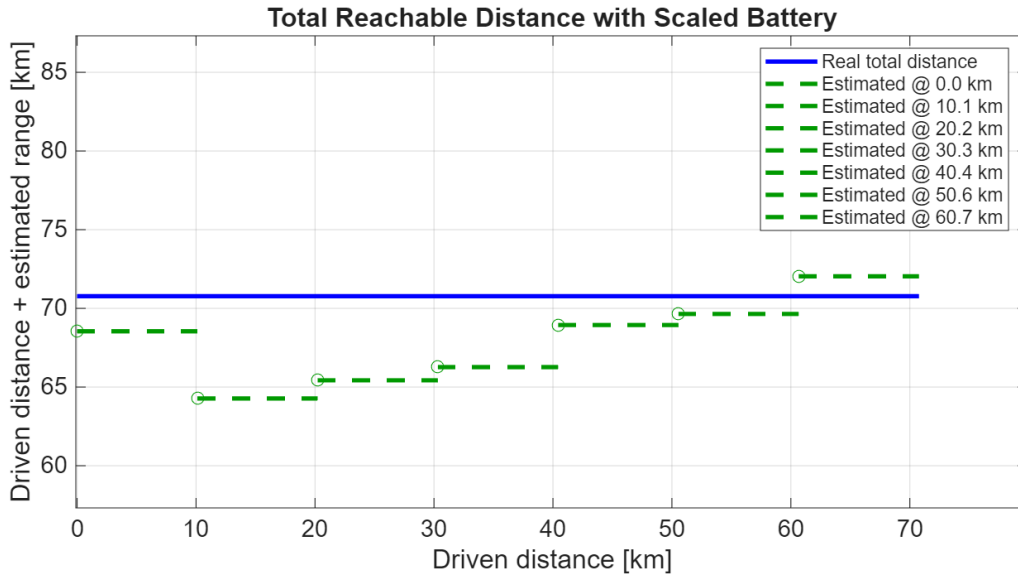


Figure 3.12: Predicted total reachable distance for the traffic congestion scenario. The battery capacity was scaled to approximately match the route length to emphasise the influence of the traffic disturbance.

the prediction by incorporating the actual vehicle state, but the magnitude of the correction is considerably smaller than that observed in the vehicle mass scenarios. The results indicate that, for the investigated route and vehicle configuration, the estimator is more sensitive to errors in vehicle mass than to the introduced traffic congestion. Nevertheless, the scenario demonstrates how unexpected traffic events can be incorporated into the re-estimation framework and how updated vehicle information can be used to continuously refine route-based energy predictions during operation.

3.4.2 Traffic Information Available Before Departure

In this scenario, the traffic congestion was included in the route data before the initial prediction was generated. This represents a situation where real-time traffic information is available from external sources, such as HERE traffic services, before departure. Consequently, both the predictive energy estimator and the TruckMaker simulation were provided with the same traffic conditions throughout the route.

Figure 3.13 shows that both the estimated and simulated vehicle speed profiles capture the low-speed section caused by the traffic congestion. Unlike the previous scenario, where the estimator assumed normal traffic conditions, the congestion is now included in the initial prediction. As a result, the estimator correctly anticipates the reduced vehicle speed within the affected road segment.

It should be noted, however, that the estimated vehicle speed remains noticeably higher than the TruckMaker reference throughout the congestion section and does not fully reach the imposed speed limit of 10 km/h. This behaviour is related to a limitation of the current estimator formulation at very low vehicle speeds. Since distance is used as the independent variable in the model, several model relations become increasingly sensitive as the vehicle speed approaches zero, with the for-

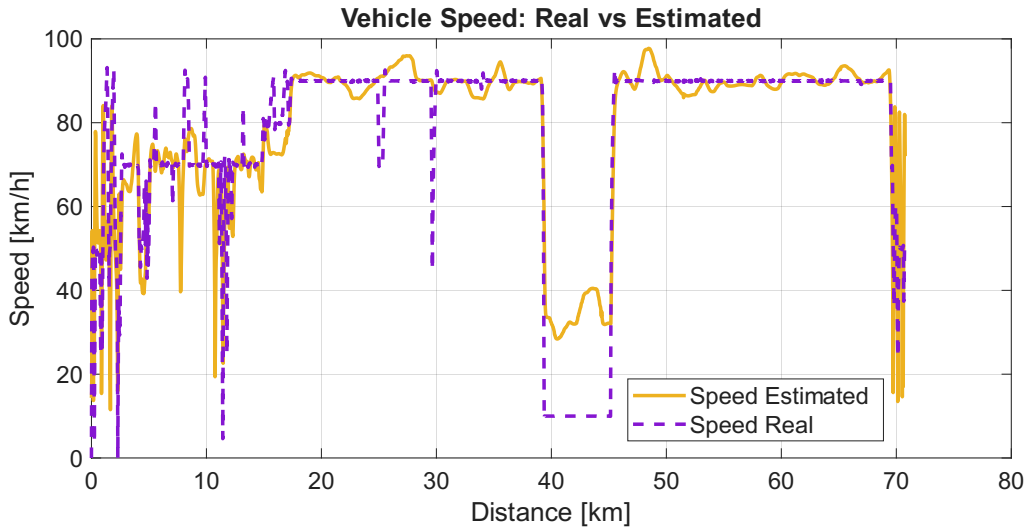


Figure 3.13: Vehicle speed profile when traffic congestion is included in both the estimator and the TruckMaker simulation before departure.

mulation becoming singular at zero speed. With the parameterization used in this model, the speed-generation model therefore becomes less suitable for representing very low-speed driving conditions.

A predicted speed of approximately 30 km/h was nevertheless considered acceptable for the purpose of the present energy-estimation study, since the aerodynamic contribution to the total driving resistance is comparatively small in this low-speed region. The TruckMaker simulations had also been completed before this limitation of the estimator was identified. The existing simulation cases were therefore used rather than repeating the complete simulation study with a modified speed-generation model. Consequently, the traffic scenario should primarily be interpreted as a demonstration of how traffic information can be introduced into the development environment, rather than as an accurate representation of very low-speed traffic behavior.

The resulting SOC predictions are shown in Figure 3.14. Compared with the previous scenario, where the congestion was unknown, the initial prediction is now based on a more representative description of the route. Despite the inclusion of the traffic information, the overall SOC evolution remains similar to that observed in the unexpected congestion scenario. This observation is consistent with the results presented in the previous section, which indicated that the introduced traffic disturbance has only a small influence on the total vehicle energy consumption. As a result, the difference between the two traffic scenarios remains relatively small.

The same behaviour can be observed in Figure 3.15, which presents the predicted total reachable distance throughout the route. The predicted range remains relatively close to the TruckMaker reference throughout the journey and gradually converges towards the final value as re-estimations are performed.

Comparing the results of this scenario with those presented in Section 3.4.1 reveals an unexpected outcome. While the traffic congestion had only a minor influence on the TruckMaker simulation results, the predictive energy estimator exhibits a

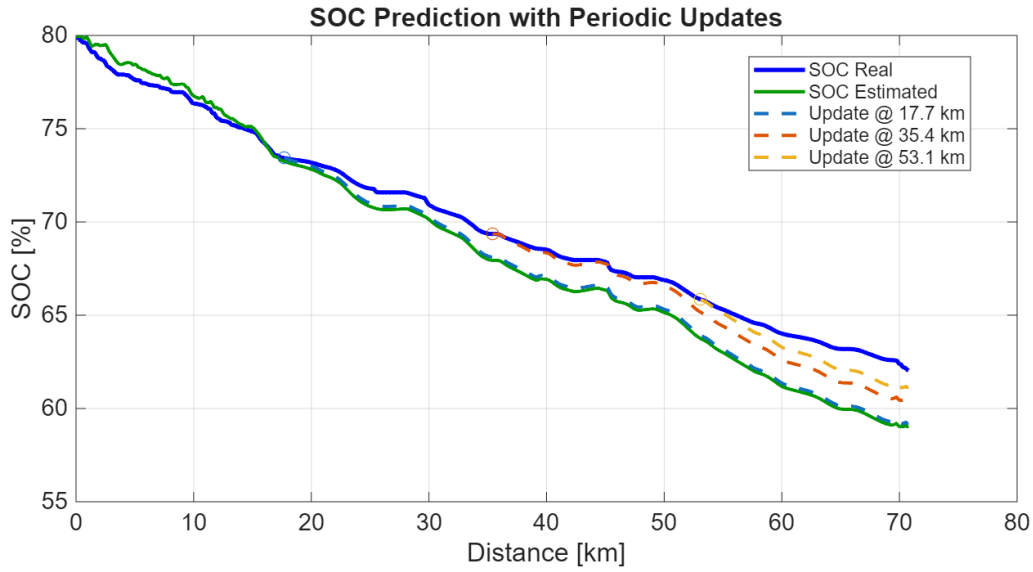


Figure 3.14: SOC prediction throughout the route when traffic information is available before departure.

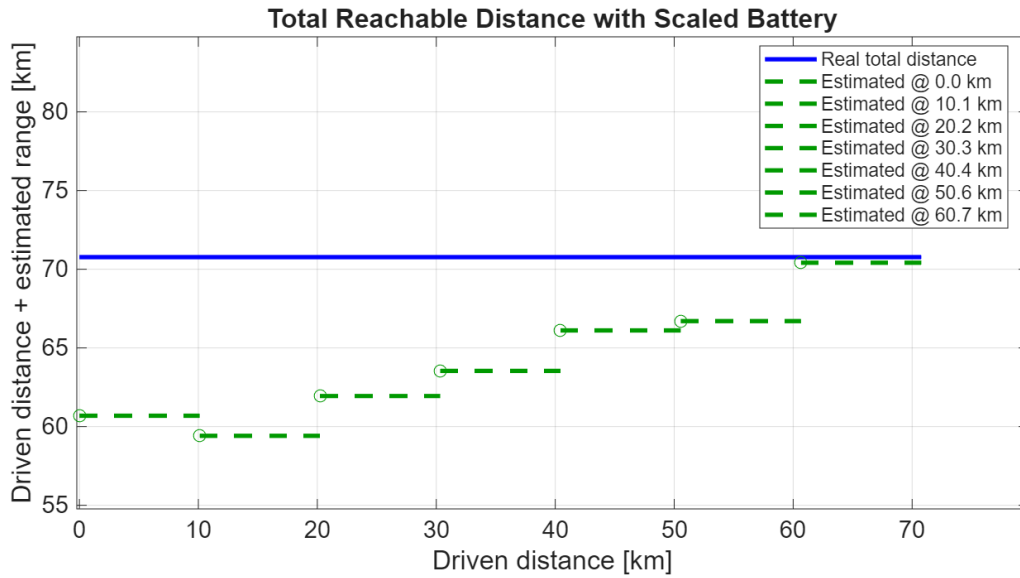


Figure 3.15: Predicted total reachable distance when traffic information is available before departure. The battery capacity was scaled to approximately match the route length to emphasise the influence of the traffic disturbance.

noticeably larger response when the congestion information is included in the initial prediction. Consequently, the estimated energy consumption increases, and the resulting SOC and range predictions deviate further from the TruckMaker reference than in the case where the congestion was unknown.

This behaviour suggests that the estimator may be more sensitive to the imposed traffic disturbance than the TruckMaker vehicle model. As a result, including the congestion information in the initial prediction does not improve the prediction accuracy for the investigated route. Instead, the prediction error increases compared

with the scenario where the estimator assumes normal traffic conditions.

One possible explanation is that the simplified representation of the traffic queue within the speed generation model causes the estimator to overestimate the impact of the congestion on vehicle energy consumption. Since the speed generation algorithm forms part of the underlying research estimator, further investigation would be required to determine whether the observed behaviour originates from the modelling assumptions or from limitations in the implementation of the traffic scenario.

Nevertheless, the results demonstrate that the quality of the underlying traffic model is crucial when incorporating traffic information into route-based energy prediction. In this particular case, access to traffic information before departure does not lead to improved prediction accuracy and instead produces a larger deviation from the TruckMaker reference.

3.5 Driver Parameter Identification

The influence of the driver-related parameters K and $\sigma_{v,\text{ref}}$ was investigated through parameter identification and sensitivity analyses. Their effects on predicted energy consumption, uncertainty, and SOC were evaluated.

3.5.1 Influence of Driver Parameter K

The driver parameter K was identified using data from the first half of the route according to the method described in Section 2.7. The resulting value was

$$K = 3198.9 \text{ Ns/m.} \quad (3.3)$$

To investigate the sensitivity of the energy prediction to the driver parameter, the route was evaluated for a range of different K values. The resulting mean energy consumption is shown in Figure 3.16.

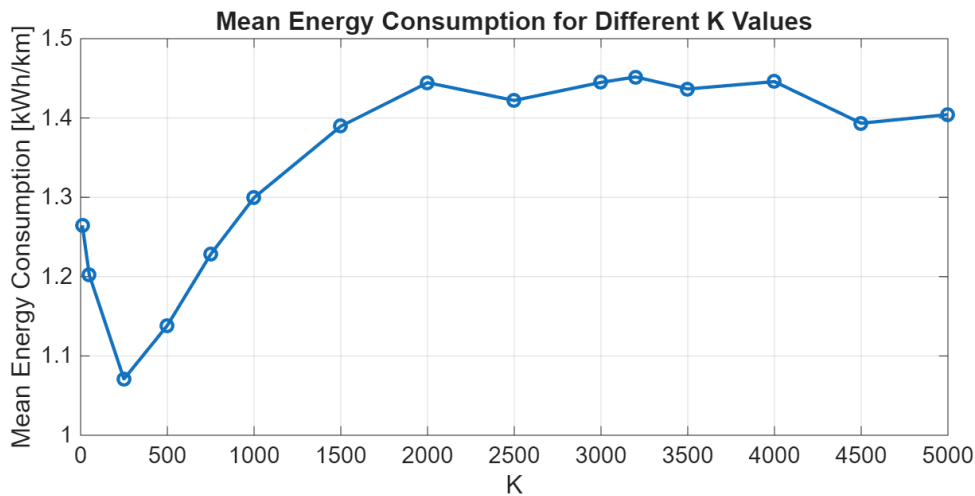


Figure 3.16: Mean predicted energy consumption for different values of the driver parameter K .

The results show that K has a noticeable influence on the predicted energy consumption at low parameter values. However, very low values of K are not desirable, since a lower K corresponds to a weaker driver response to deviations between the reference and actual vehicle speed, resulting in poorer tracking of the reference speed. Above approximately 1500 Ns/m, the mean energy consumption remains within a relatively narrow range of approximately 1.39–1.45 kWh/km. The identified value of $K = 3198.9$ Ns/m therefore lies within a region where the predicted mean energy consumption is relatively insensitive to further changes in K .

The influence of K on the predicted energy uncertainty was also investigated. The energy uncertainty was calculated as half the difference between the upper and lower energy bounds and averaged along the route. The result is shown in Figure 3.17.

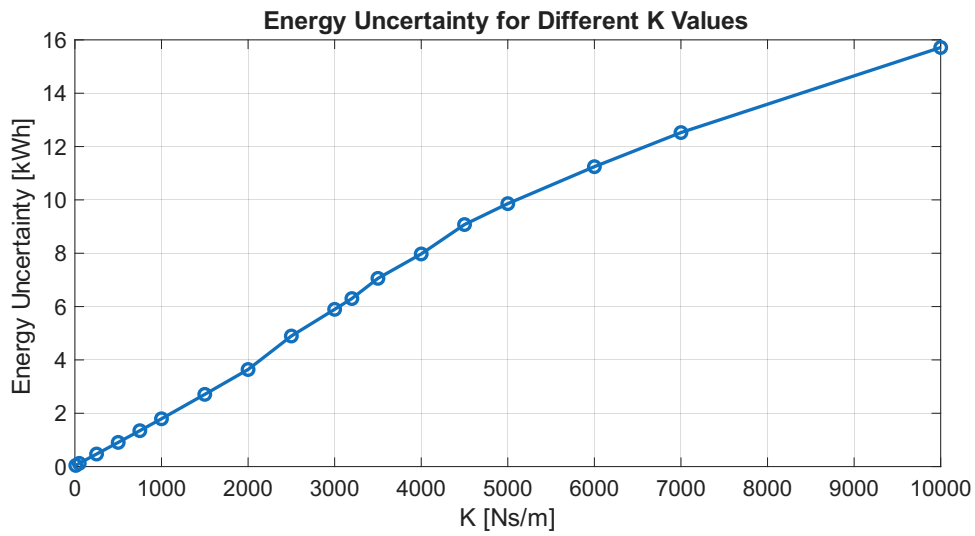


Figure 3.17: Mean predicted energy uncertainty for different values of the driver parameter K .

Unlike the mean energy consumption, the predicted energy uncertainty increases continuously with increasing K . This is consistent with the proportional driver model, where a larger K gives a stronger force response to deviations between the reference and actual vehicle speed. Consequently, uncertainty in the speed difference can result in larger variations in the predicted force and energy demand.

To evaluate whether adapting the driver parameter based on previously driven data improves the prediction, the identified value was applied to the second half of the route. The resulting SOC prediction was compared with the original estimator configuration and the TruckMaker reference, as shown in Figure 3.18.

The SOC prediction obtained using the identified K value is almost identical to the original prediction throughout the second half of the route. The two estimated SOC trajectories overlap for nearly the complete distance and show a similar deviation from the TruckMaker reference.

Together, the results show that K has limited influence on mean energy consumption and SOC prediction once it exceeds approximately 1500 Ns/m, while the predicted energy uncertainty continues to increase with increasing K . Updating K to the value identified from the first half of the route therefore did not noticeably improve

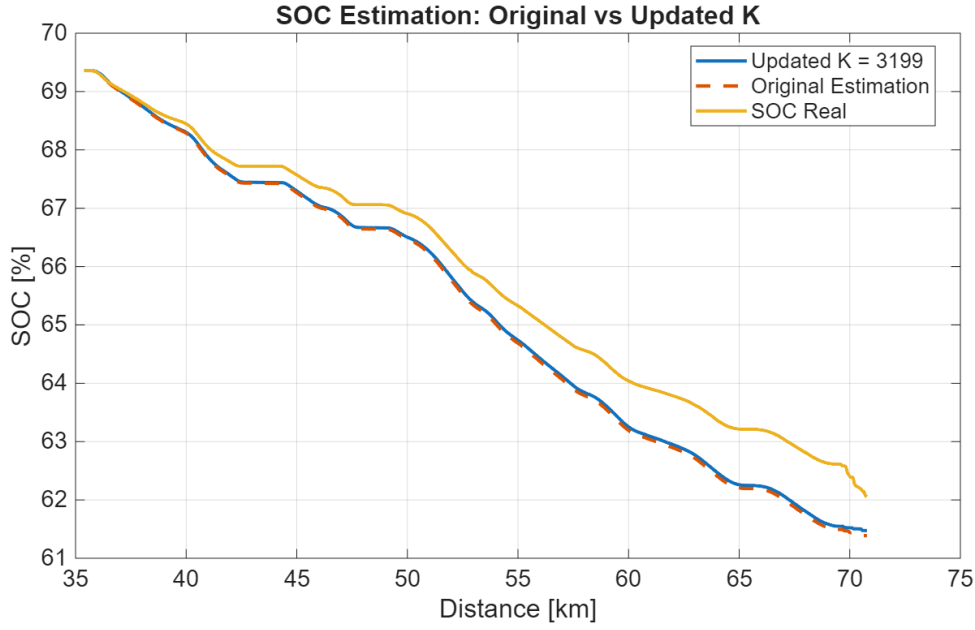


Figure 3.18: SOC prediction during the second half of the route using the original estimator configuration and the updated driver parameter $K = 3199$ Ns/m, compared with the TruckMaker reference.

the SOC prediction for the investigated case.

3.5.2 Influence of Reference-Speed Uncertainty $\sigma_{v,\text{ref}}$

In addition to the driver response parameter K , the variation in the reference-speed error was estimated from the first half of the route. The resulting value was

$$\sigma_{v,\text{ref}} = 2.6306 \text{ m/s.} \quad (3.4)$$

To investigate the sensitivity of the energy prediction to $\sigma_{v,\text{ref}}$, the estimator was evaluated for a range of different parameter values. The resulting mean energy consumption is shown in Figure 3.19.

The mean energy consumption decreases as $\sigma_{v,\text{ref}}$ increases. The reduction is most pronounced at lower parameter values and becomes smaller for larger values of $\sigma_{v,\text{ref}}$. A possible explanation is that a larger reference-speed uncertainty reduces the influence of short-term deviations in the reference speed on the predicted vehicle response, resulting in a smoother and less aggressive speed profile. This can reduce the energy required for acceleration and therefore lower the predicted mean energy consumption. The identified value of 2.63 m/s is located within the middle of the investigated range.

The influence of $\sigma_{v,\text{ref}}$ on the predicted energy uncertainty was also investigated. Figure 3.20 shows the energy uncertainty at the destination for the investigated parameter values.

The energy uncertainty increases continuously with increasing $\sigma_{v,\text{ref}}$, as shown in Figure 3.20. The observed trend is consistent with the relationship

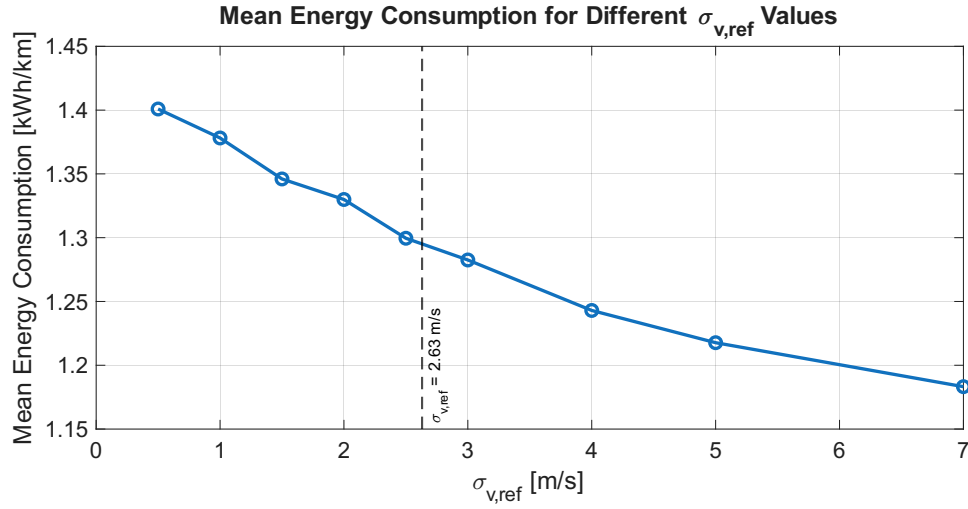


Figure 3.19: Mean predicted energy consumption for different values of $\sigma_{v,ref}$. The dashed line indicates the value identified from the first half of the route.

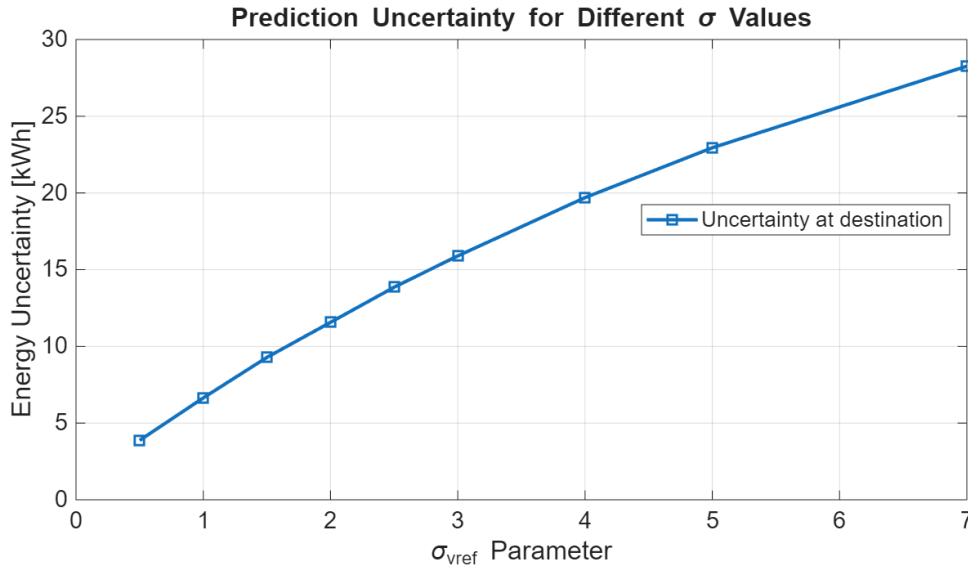


Figure 3.20: Predicted energy uncertainty at the destination for different values of $\sigma_{v,ref}$.

$$\sigma_E = C \sqrt{\sigma_{v,ref}}, \quad (3.5)$$

where σ_E represents the energy uncertainty and C is a proportionality constant. The results therefore show that increasing $\sigma_{v,ref}$ leads to an increased energy prediction uncertainty, following the expected trend of the uncertainty model.

To evaluate the influence of the identified parameter on the SOC prediction, $\sigma_{v,ref} = 2.63$ m/s was applied to the second half of the route. The resulting prediction was compared with the original estimator configuration and the TruckMaker reference, as shown in Figure 3.21.

The SOC prediction obtained using the identified value of $\sigma_{v,ref}$ is almost identical to the original prediction. The two estimated trajectories overlap throughout most

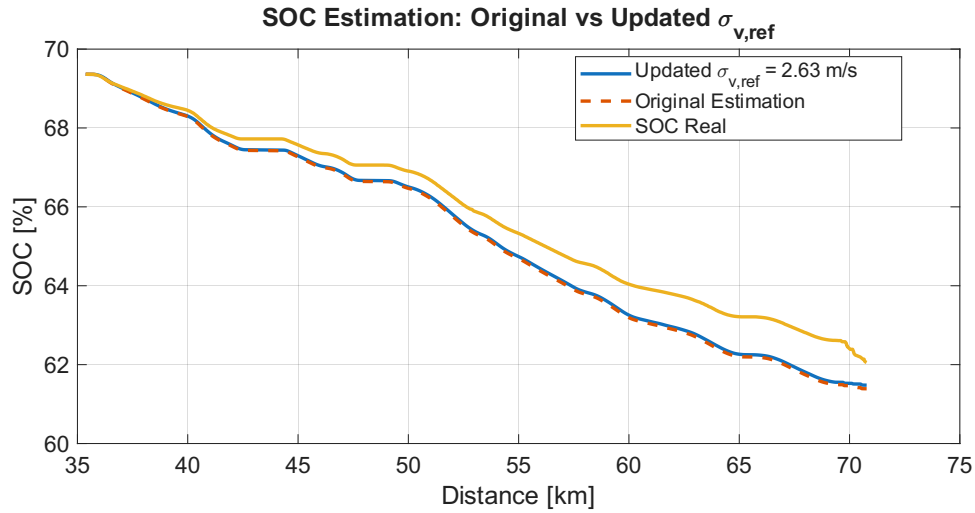


Figure 3.21: SOC prediction during the second half of the route using the original estimator configuration and the updated value $\sigma_{v,\text{ref}} = 2.63 \text{ m/s}$, compared with the TruckMaker reference.

of the second half of the route and show a similar deviation from the TruckMaker reference.

Together, the results show that $\sigma_{v,\text{ref}}$ has a clear influence on both the predicted mean energy consumption and the associated uncertainty. Increasing the parameter reduces the mean predicted energy consumption while simultaneously increasing the uncertainty of the prediction. However, replacing the original parameter with the value identified from the first half of the route did not result in a noticeable change in the SOC prediction for the investigated case. The main influence of $\sigma_{v,\text{ref}}$ is therefore observed in the predicted uncertainty rather than in the resulting SOC trajectory around the identified parameter value.

4

Conclusion and Discussion

This thesis developed and demonstrated a simulation-based development and evaluation environment for route-based predictive vehicle functions. The environment integrates route and mission data, a predictive energy estimator, TruckMaker vehicle simulation, and MATLAB-based post-processing, enabling predicted vehicle behaviour to be systematically compared with a simulated reference under controlled and repeatable conditions.

Predictive range estimation for a battery-electric heavy vehicle was used as the primary application to demonstrate and evaluate the developed environment. The performed studies therefore provide two types of conclusions: conclusions regarding the capabilities of the development environment, and results specific to the investigated predictive range estimator.

4.1 Development Environment

The developed environment enabled the predictive range estimator to be integrated with route, mission, and vehicle information and evaluated against a TruckMaker reference. Vehicle and route parameters could be modified in a controlled manner, while MATLAB-based post-processing enabled evaluation of SOC, driving range, prediction uncertainty, and re-estimation behaviour.

The investigated scenarios demonstrate that the environment can be used to study both nominal estimator performance and sensitivity to changing or uncertain conditions. Incorrect vehicle mass, traffic disturbances, re-estimation frequency, and driver-related estimator parameters could be varied independently while the remaining test conditions were kept consistent. This provides a repeatable framework for developing and evaluating route-based predictive functions before moving towards testing in a physical vehicle.

4.2 Accuracy of the predictive range estimator

The results obtained in this thesis demonstrate that the predictive range estimator is capable of accurately estimating vehicle energy consumption and state of charge for the investigated route and vehicle configuration. Under nominal operating conditions, the estimated SOC showed good agreement with the TruckMaker reference throughout the route, with only minor deviations observed between the predicted and simulated vehicle behaviour.

The comparison of vehicle speed profiles showed that the estimator was able to capture the overall driving behaviour of the route, particularly along the highway sections where vehicle speed remained close to the posted speed limits. Since vehicle speed is one of the most influential factors affecting vehicle energy consumption, the ability to generate a representative speed profile forms an important basis for accurate energy prediction.

The estimated SOC followed the TruckMaker reference closely over the complete route. Although the estimator exhibited a slightly steeper SOC gradient, resulting in a small overestimation of the total energy consumption, the final SOC prediction remained close to the simulated value. Furthermore, the TruckMaker reference closely remained within the estimated uncertainty bounds throughout the route, indicating that the uncertainty estimation provided a realistic representation of the prediction confidence.

The re-estimation study further demonstrated that the prediction accuracy improved as additional vehicle information became available during the trip. Shorter re-estimation intervals generally resulted in closer agreement with the TruckMaker reference, while longer intervals allowed prediction errors to accumulate over greater distances. Nevertheless, all investigated update intervals converged towards the correct destination SOC as the vehicle approached the end of the route.

Overall, the results indicate that the predictive range estimator provides accurate and robust route-based energy predictions for battery electric heavy-duty vehicles. The combination of route information, energy estimation, uncertainty quantification, and periodic re-estimation enables reliable predictions of both state of charge and remaining driving range throughout a journey.

4.3 Influence of vehicle and route parameters

The investigated disturbance scenarios demonstrated that the predictive range estimator is sensitive to both vehicle-specific and route-specific parameters. However, the results indicate that the influence of these parameters varies considerably depending on the type of uncertainty introduced.

Among the evaluated parameters, vehicle mass was found to have the largest impact on prediction accuracy. When the estimator assumed a gross combination weight of 23 tonnes instead of the reference value of 19 tonnes, a noticeable increase in predicted energy consumption was observed. This resulted in lower predicted SOC values and a significant underestimation of the total reachable distance. The results show that vehicle mass is a critical input parameter for route-based energy prediction, as it directly affects the energy required for acceleration, climbing road gradients, and rolling resistance.

The mass correction scenario further demonstrated the importance of accurate vehicle information. When the correct vehicle mass was introduced during the route, the subsequent predictions moved significantly closer to the TruckMaker reference. This indicates that the re-estimation framework can effectively compensate for incorrect vehicle parameters when updated information becomes available during operation. In contrast, the investigated traffic congestion scenario had a relatively small influence on the overall vehicle energy consumption in the TruckMaker simulation.

Although a prolonged low-speed section was introduced, the resulting changes in SOC and reachable distance remained modest compared with those observed in the vehicle mass scenarios. This suggests that, for the investigated route and vehicle configuration, vehicle mass has a greater influence on prediction accuracy than the introduced traffic disturbance.

Interestingly, when traffic information was included in the estimator before departure, the prediction accuracy did not improve. Instead, the estimator predicted a larger increase in energy consumption than was observed in the TruckMaker simulation, resulting in larger deviations from the reference case. This behaviour indicates that the accuracy of route-based energy prediction depends not only on the availability of route information, but also on how that information is represented within the prediction model. Consequently, accurate modelling of traffic conditions appears to be as important as access to the traffic information itself.

The investigated driver-model parameters showed different effects on the predicted mean energy consumption and its associated uncertainty. The driver response parameter K had a noticeable influence at low values, where a weaker driver response also resulted in poorer tracking of the reference speed. Above approximately 1500 Ns/m, however, further changes in K produced only minor differences in mean energy consumption and SOC prediction. In contrast, the predicted energy uncertainty continued to increase with increasing K . This indicates that, within the investigated range, K mainly affects the driver response and the magnitude of the predicted uncertainty once a sufficiently strong speed-tracking response has been reached.

The reference-speed uncertainty, $\sigma_{v,\text{ref}}$, had a clearer influence on the uncertainty prediction. Increasing $\sigma_{v,\text{ref}}$ resulted in a larger predicted energy uncertainty, while the mean predicted energy consumption decreased. The parameter can therefore be interpreted as an important tuning parameter for the uncertainty representation of the estimator. However, replacing the original values of either K or $\sigma_{v,\text{ref}}$ with the values identified from the first half of the route did not noticeably improve the SOC prediction for the second half. This suggests that the original parameter values were already located in a region where the nominal SOC prediction was relatively insensitive to further parameter adaptation.

For the investigated route and operating conditions, the vehicle mass had a substantially larger influence on the nominal SOC and range prediction than the adaptation of the driver-model parameters. Nevertheless, the parameter study shows that K and $\sigma_{v,\text{ref}}$ can be used to influence different aspects of the estimator, particularly the balance between the expected prediction and its associated uncertainty.

It should also be noted that neither the predictive energy estimator nor the TruckMaker post-processing calculations considered auxiliary energy consumption. Consequently, only the traction-related battery energy consumption was included in the analysis. In real-world operation, a prolonged traffic congestion would increase the total trip duration, resulting in additional energy consumption from auxiliary systems such as cabin climate control, lighting, displays, electronic control units, and other onboard electrical equipment. For long-lasting low-speed traffic conditions, these auxiliary loads may contribute significantly to the total battery energy consumption.

Furthermore, the traffic congestion was represented as a road segment with a constant low speed limit of 10 km/h. In practice, traffic queues are rarely characterised by constant-speed driving and instead consist of repeated acceleration and braking events as vehicles move through stop-and-go traffic. Such behaviour influences the vehicle energy consumption and may produce different results than those obtained in this study. Although regenerative braking can recover part of the kinetic energy, the additional acceleration events would still affect the overall energy demand.

Therefore, the relatively small impact of the investigated traffic congestion on the prediction results may partly be explained by the simplified traffic representation and the omission of auxiliary energy consumption. Incorporating auxiliary loads and more realistic stop-and-go traffic behaviour in future studies could increase the sensitivity of the energy prediction to traffic-related disturbances and provide a more realistic representation of real-world vehicle operation.

4.4 Effect of re-estimation frequency

The results of this thesis demonstrate that periodic re-estimation can significantly improve the accuracy of route-based energy predictions. By updating the prediction using the current vehicle state of charge, the estimator is able to compensate for accumulated modelling errors and reduce the discrepancy between predicted and actual vehicle behaviour.

For all investigated update intervals, the destination SOC prediction gradually converged towards the TruckMaker reference as the vehicle progressed along the route. This behaviour confirms that re-estimation provides a mechanism for continuously correcting the prediction based on observed vehicle performance rather than relying solely on the initial route prediction.

The influence of the update interval was most apparent during the first half of the route. Shorter update intervals generally produced predictions that followed the TruckMaker reference more closely, while longer intervals allowed prediction errors to persist for a greater distance before being corrected. Consequently, more frequent updates resulted in a more accurate representation of the actual vehicle energy consumption throughout the journey.

However, the improvement obtained from increasingly frequent updates was found to diminish beyond a certain point. Simulations using update intervals shorter than 8750 m showed only minor additional improvements compared with the shortest interval presented in the results. Furthermore, the prediction curves became increasingly difficult to distinguish visually due to their close agreement with the reference case. This indicates that very frequent re-estimation may provide limited practical benefits relative to the increased computational effort and system complexity.

The re-estimation framework also proved effective when operating conditions changed during the route. In the vehicle mass correction scenario, updating the estimator with the correct vehicle mass significantly reduced the prediction error compared with maintaining the incorrect mass assumption throughout the journey. This demonstrates that re-estimation not only improves prediction accuracy under nominal conditions but also enables the estimator to adapt when new vehicle information becomes available.

Overall, the results show that re-estimation is a key component of predictive range estimation systems. By continuously incorporating updated vehicle information, the estimator becomes more robust to modelling uncertainties and changing operating conditions, resulting in more reliable predictions of state of charge and remaining driving range.

4.5 Future Work

Although the results presented in this thesis demonstrate the potential of route-based predictive range estimation for battery electric heavy-duty vehicles, several areas remain for future investigation and development.

The most important extension of the present work is validation using real vehicle data. The evaluation performed in this thesis was based on TruckMaker simulations, which provide a controlled environment for testing the estimator. Future studies should compare the estimator predictions with measurements collected from vehicles operating under real-world conditions in order to evaluate the model accuracy in practical applications.

Another area for future work is the incorporation of auxiliary energy consumption. The current implementation only considers traction-related battery energy consumption. In reality, systems such as cabin climate control, lighting, displays, electronic control units, and battery thermal management consume energy independently of vehicle motion. These loads become particularly important during low-speed operation and traffic congestion, where the trip duration increases while the vehicle covers relatively little distance. Including auxiliary energy consumption could therefore improve the realism of the energy prediction model.

The representation of traffic conditions could also be further refined. In this study, traffic congestion was modelled as a road segment with a reduced speed limit. Real traffic queues are typically characterised by stop-and-go behaviour involving repeated acceleration and braking events. Future work could investigate more advanced traffic models capable of representing dynamic vehicle interactions and varying traffic densities. Such improvements may provide a more realistic assessment of how traffic disturbances influence vehicle energy consumption and prediction accuracy.

Further research could also investigate the influence of additional vehicle and environmental parameters. Examples include varying payload distributions, trailer configurations, wind conditions, road surface conditions, and ambient temperature. Evaluating a wider range of operating conditions would improve the understanding of which factors most strongly affect prediction accuracy.

The traffic information results obtained in this study suggest that additional work may be required to improve the integration of traffic data into the predictive energy estimator. While traffic information was successfully incorporated into the route description manually, the resulting prediction did not improve for the investigated scenario. Future studies should therefore examine how traffic-related information is represented within the speed generation and energy prediction models to ensure that the estimator responds realistically to traffic disturbances.

Finally, the re-estimation framework could be extended to utilise real-time vehicle

and cloud-based information sources. By continuously incorporating updated route, weather, traffic, and vehicle data, future predictive range estimation systems may provide more accurate and robust predictions throughout a journey. Such functionality could contribute to improved route planning, reduced range anxiety, and more efficient operation of battery-electric heavy vehicles.

4.5.1 Integration with a Physical Vehicle

A natural next step would be to integrate the predictive range estimator with a physical research vehicle, such as the REVERE truck. This would enable the estimator to be evaluated using measured vehicle signals under real driving conditions instead of relying only on simulation data.

As illustrated in Figure 4.1, vehicle signals could be accessed through the truck CAN network via a gateway and CAN adapter. Additional instrumentation, such as GPS, IMU, weather sensors, cameras, articulation-angle sensors, and trailer CAN signals, could provide complementary information. The signals could then be transferred to a connected computer for logging, decoding, and online processing by the predictive estimator.

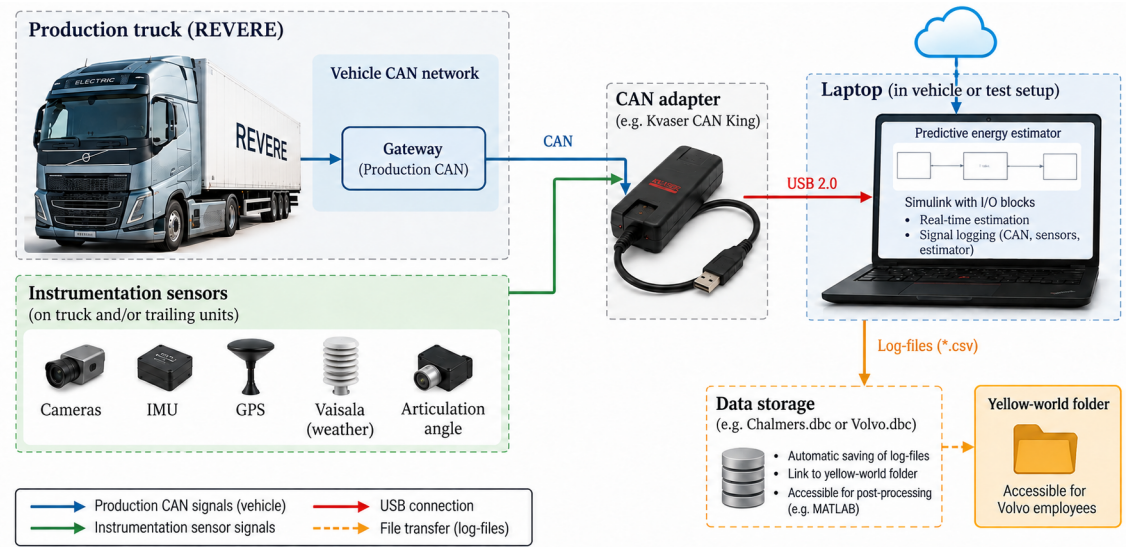


Figure 4.1: Concept for integrating the predictive energy estimator with a physical REVERE research vehicle using vehicle CAN signals, additional instrumentation, a CAN adapter, and an external computer for real-time estimation and data logging.

Such an implementation would allow the predicted energy consumption, SOC, and remaining range to be continuously updated using measured vehicle data. It would also make it possible to investigate practical aspects such as signal availability, measurement noise, communication delays, and real-time computational requirements.

Bibliography

- [1] European Environment Agency (2025). Sustainability of Europe’s Mobility Systems 2025: Climate. <https://www.eea.europa.eu/en/analysis/publications/sustainability-of-europes-mobility-systems-2025/climate>
- [2] European Parliament and Council of the European Union (2024). Regulation (EU) 2024/1610 of the European Parliament and of the Council of 14 May 2024 amending Regulation (EU) 2019/1242 as regards strengthening the CO₂ emission performance standards for new heavy-duty vehicles. <https://eur-lex.europa.eu/eli/reg/2024/1610/oj>
- [3] International Energy Agency (2026). Global EV Outlook 2026. <https://www.iea.org/reports/global-ev-outlook-2026>
- [4] Scherrer, A., Ziemsky, V. and Ertelt, S.-M. (2026). From early adopters to early majority: Barriers and policy support needs for battery-electric truck adoption in Germany and Sweden. *Transport Policy*, 181, 104076. <https://doi.org/10.1016/j.tranpol.2026.104076>
- [5] Basso, R., Kulcsár, B., Egardt, B., Lindroth, P. and Sanchez-Diaz, I. (2019). Energy consumption estimation integrated into the Electric Vehicle Routing Problem. *Transportation Research Part D: Transport and Environment*, 69, 141–167. <https://doi.org/10.1016/j.trd.2019.01.006>
- [6] Alonso-Villar, A., Davíðsdóttir, B., Stefánsson, H., Ásgeirsson, E. I. and Kristjánsson, R. (2023). Electrification potential for heavy-duty vehicles in harsh climate conditions: A case study based technical feasibility assessment. *Journal of Cleaner Production*, 417, 137997. <https://doi.org/10.1016/j.jclepro.2023.137997>
- [7] Emvin, C., Romano, L., Bruzelius, F., Jacobson, B., Johannesson, P. and Andersson, R. (2026). A Kalman-smoother-based known route energy demand predictor for road vehicles. *IEEE Transactions on Intelligent Transportation Systems*. <https://doi.org/10.1109/TITS.2026.3728097>
- [8] IPG Automotive GmbH. TruckMaker: Real-Time Simulation of Heavy-Duty Vehicles. https://www.ipg-automotive.com/fileadmin/data/know-how/media_library/pdf/IPG_Automotive_TruckMaker_Product_Sheet_EN.pdf Accessed September 2026.
- [9] Berzi, L. et al. (2021). Major barriers in adoption of electric trucks in logistics. https://www.researchgate.net/publication/357042804_Major_Barriers_in_Adoption_of_Electric_Trucks_in_Logistics_System
- [10] Emvin, C. et al. (2024). A propulsion energy estimator for road vehicles. <https://research.chalmers.se/publication/543383>

- [11] U-Feel Project Documentation, Chalmers University of Technology (2022–2025). <https://research.chalmers.se/en/project/11005>
- [12] Hyttinen, J. (2023). Modelling and experimental testing of truck tyre rolling resistance. Doctoral thesis, KTH Royal Institute of Technology. <https://kth.diva-portal.org/>

A

Appendix 1

.1 Python Script for Data Preprocessing

```
1 import pandas as pd
2 import numpy as np
3 from scipy.interpolate import interp1d
4 import os
5
6 directory = r>Data/logfiles/"
7 csv_files = []
8
9 for file in os.listdir(directory):
10     if file.endswith(".csv") and not file.startswith("eqd_"):
11         csv_files.append(file)
12
13 for filename in csv_files:
14     csv_file = directory + filename
15     df = pd.read_csv(csv_file)
16
17     x_column_name = 'Distance'
18     x_values = df[x_column_name].values
19
20     x_new = np.arange(x_values.min(), x_values.max(), step=25)
21
22     df_interpolated = pd.DataFrame({x_column_name: x_new})
23
24     for col in df.columns:
25         if col == x_column_name:
26             continue
27
28         # Boolean / 0-1 columns
29         if df[col].dtype == bool or set(df[col].dropna().unique()).issubset({0,
30 1}):
31             true_indices = np.where(df[col] == True)[0]
32             true_x_values = x_values[true_indices]
33
34             bool_interpolated = np.zeros_like(x_new, dtype=int)
35
36             for true_x in true_x_values:
37                 closest_new_x_idx = np.argmin(np.abs(x_new - true_x))
38                 bool_interpolated[closest_new_x_idx] = 1
39
40             df_interpolated[col] = bool_interpolated.astype(bool)
```

```
41     # Numeric columns
42     elif pd.api.types.is_numeric_dtype(df[col]):
43         f_interp = interp1d(
44             x_values,
45             df[col].values,
46             kind='linear',
47             fill_value="extrapolate"
48         )
49         df_interpolated[col] = f_interp(x_new)
50
51     # Text/date columns
52     else:
53         df_interpolated[col] = df[col].iloc[0]
54
55     output_file = directory + 'eqd_' + filename
56     df_interpolated.to_csv(output_file, index=False)
57
58     print("Interpolation completed:", output_file)
```

Listing 1: Python script used for data preprocessing

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