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Introducing fine grained energy consumption variables into a public passenger transport simulation in SUMO

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Abstract

Improving energy efficiency in public passenger transport is key to achieving sustainability goals. In many developing countries, public passenger transport relies heavily on fossil fuels, which necessitates a strong focus on reducing emissions from energy consumption. Surprisingly, few studies have addressed this issue in the context of daily operations, with most research focusing on operational and infrastructural changes. This paper aims to fill this gap by introducing detailed energy consumption variables into a public transport simulation model using SUMO, a tool known for its seamless integration with Python. The development of two Python scripts underpins this endeavour. The first script facilitates the automatic generation of scenarios, allowing the manipulation of parameters such as station spacing, line length, passenger capacity and waiting times, among others. The second script is dedicated to estimating energy consumption for each scenario. Together, these tools allow us to calculate average energy consumption for different scenarios and modes of public transport. As a result, they provide valuable insights for the formulation of public policies aimed at saving energy in different public transport environments and lay the foundation for the integration and development of intelligent transport systems and simulation-based digital twins.

Keywords: public transport, simulation, fine grained variables, energy consumption.

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1. Introduction

Transport simulation studies have traditionally focused on operational and infrastructure improvements. However, with the pressing need to reduce energy consumption and emissions in urban environments, there is a growing trend to incorporate energy consumption and emissions estimates into these simulations. This shift is particularly relevant in developing countries, where unique operational characteristics have a significant impact on the energy consumption of public passenger transport. These include overwhelming travel demand that exceeds existing infrastructure capacity, a diverse fleet of vehicles of varying sizes and ages, and fragmented ownership structures. As a result, manufacturers' specifications often do not match the actual energy consumption of these vehicles.

This paper addresses this challenge by introducing granular variables into simulations with the aim of improving energy consumption and emissions estimates by incorporating specific data. While traditional simulation studies cover various aspects such as configuration variations, vehicle tracking, travel plan optimisation and traffic forecasting, among others, this paper focuses on the integration and development of intelligent transport systems and simulation-based digital twins.

The paper is structured as follows: Section 2 provides a literature review on public transport, the variables influencing vehicle energy consumption, and public transport simulation to provide an overall perspective. Section 3 presents the scripts designed to incorporate fine-grained variables for energy consumption. Section 4 provides an illustrative application of the developed scripts. Finally, the paper concludes by discussing the functionality of the scripts and providing insights into the example discussed earlier.

2. Literature Review

2.1. Public passenger transport

Public transport plays a crucial role in the socio-economic fabric of the areas it serves, meeting the diverse needs of the population by facilitating travel to jobs, educational institutions, offices, medical facilities and more [1]. In urban areas, public transport carries 75 per cent of the travel burden, underlining its vital role in meeting transport demand. However, the environmental impact of the transport sector remains a major concern in the context of environmental sustainability [2].

As a major consumer of fossil fuels, the transport sector is a major contributor to emissions, making it a central element in a nation's emissions profile [3]. In particular, the longer a passenger transport vehicle remains in service, the more resources must be allocated to its maintenance and the greater the energy expenditure required to transport people [4].

In developing countries, public passenger transport is provided by collective systems that regulate routes and fares. However, the fleet consists of vehicles of different sizes and ages, reflecting fragmented ownership structures. This diversity poses operational and service quality challenges, with a direct impact on energy consumption and emissions [5].

These challenges are compounded by the high levels of motorisation in these countries and the complexities of integrating public transport into congested road networks. Factors such as increasing travel demand exceeding infrastructure capacity, heavy traffic congestion leading to slow speeds (often less than 10 kilometres per hour), inadequate road maintenance [6] and lax driver discipline with disregard for designated public transport lanes and stops all contribute to a significant escalation in energy consumption.

The predominance of a profit-oriented approach to the management of public transport, as opposed to a service-oriented approach, also has an impact on mobility. This shift leads to longer travel times and more transfers, which further reduces the quality of transport services [7] [8] [9].

2.2. Variables that impact a vehicles energy consumption

According to several authors, several factors influence the energy consumption and emissions of public passenger transport. Energy intensity, quantified as megajoules (MJ) per passenger/km or tonne/km (in terms of emissions, grams of CO_2 equivalent), is determined by a combination of two key factors: the energy required to move the vehicle and the utilisation of the vehicle's capacity [10] [11].

The energy required to move the vehicle depends on various elements such as fuel consumption, transport conditions (including traffic and geographical factors) and the specific characteristics of the vehicle, including its model and size. Meanwhile, the utilisation of vehicle capacity depends on factors such as passenger and cargo loads in individual vehicles, the relative utilisation of different vehicle types and the overall distribution of these vehicle types across the fleet [10] [12] [13] [14] [15].

In addition, changes in vehicle fuel consumption and emission rates are typically associated with changes in cruising speed, driver behaviour, acceleration patterns and road gradients. A comprehensive understanding of the effects of different speed and acceleration profiles can help to improve both fuel efficiency and emission reduction efforts [16] [17] [18] [19] [20].

According to reference [21], the main factors influencing the energy consumption of transport vehicles include the energy efficiency of the engines, operating practices (including load factors, speed and idling), environmental conditions (such as congestion and road infrastructure), fleet composition (differentiating between small and large vehicles, urban and rural environments) and cargo loads. These factors are known to play an important role in determining energy consumption.

While these methods are highly sensitive to changes in vehicle-specific parameters, such as engine fuel efficiency, they tend to neglect the way in which vehicles are used. This includes considerations such as the frequency and distance of passenger journeys, passenger loading patterns and transfers between modes. As a result, they provide limited insight into the potential changes in energy consumption and emissions within the urban passenger transport sector, as indicated in reference [22].

Therefore, it is crucial to examine non-vehicle parameters that affect consumption. Factors such as the type of road and the topography over which a journey is made can have a significant impact on the fuel consumption of a vehicle. Meteorological conditions also have an impact on fuel consumption, both directly and by forcing changes in driving behaviour. Effective maintenance of a vehicle's engine is another key factor that has a significant impact on fuel consumption.

In addition, the load carried by a vehicle, including the weight it carries, has a direct effect on its consumption due to the increased power demand from the engine resulting from the higher vehicle weight, which in turn affects rolling resistance, as noted in references [23], [24] and [25].

To develop an accurate energy consumption model, it is therefore essential to take into account a wide range of variables. This requires the characterisation of the fleet, which is invaluable in calculating the fuel consumption of the entire fleet. Route characterisation is equally important as it provides data such as trip duration, total distance travelled per cycle for each route, occupancy rates, time data, distance travelled during each trip and the number of buses. This information can be used to determine various variables such as average occupancy, estimated daily occupancy, fleet fuel consumption, passengers per kilometre travelled and passengers per gallon of fuel, as described in reference [26].

2.3 *Simulation on public passenger transport*

Simulation serves as a means of encapsulating the characteristics of a real-world system within a mathematical or visual abstraction, primarily when direct manipulation in the real world is impractical. Various simulation methods are used to achieve this, each providing a framework for representing a real-world system in its model form. Currently, three different modelling methods are used for simulation, with the choice depending on the specific system under study and the purpose of modelling [27] [28]:

1. System dynamics: This method is designed to study dynamic systems from an endogenous perspective. It conceptualizes the system as a causally closed structure in which the behavior of the system is internally defined by feedback loops, thereby establishing circular causality within the system.
2. Discrete event modelling: In this approach, the system is represented as a sequence of operations performed by entities. These operations include various facets such as delays, resource utilization, selection of process paths, partitioning of entities, combination of operations, and others. It is particularly suited to systems characterized by discrete, event-driven interactions.

1. Agent-based modelling: This method relies on understanding the individual behaviour of system components. It allows modelling without a complete understanding of how the whole system works, its key variables or the interdependencies between them. Instead, it focuses on the behaviours and interactions of individual agents within the system.

These three modelling methods essentially represent different perspectives that a modeller can adopt when translating a real-world system into its model representation. The choice between these methods depends on the objectives of the simulation project, the available data and the inherent nature of the system being modelled. Different simulation problems may require the use of different modelling methods.

In cases where the system does not fit perfectly into a single modelling paradigm, hybrid approaches come into play. These approaches combine two or more methods to produce a more comprehensive and adaptable model [27].

Simulation studies in the field of public transport have been used for a variety of purposes, including estimating capacity for different configurations [29], monitoring vehicle systems to track arrivals [30], optimizing travel plans [31], integrating macroeconomic, energy supply and demand, and environmental modules [32], predicting traffic patterns under different conditions [33], supporting comprehensive transport systems [34], reducing bus waiting times [35], and incorporating energy considerations into simulations [36], among others.

It is evident that the use of public transport simulation has primarily focused on operational improvements, infrastructure adaptations, and travel time reductions. However, energy consumption has not been a central aspect of these simulation studies. Therefore, there is an urgent need to incorporate fine-grained variables related to energy consumption into the simulation process to accurately characterize public passenger transport, especially in developing countries. Such an improvement will enable simulations to provide accurate estimates and suggest effective improvement measures.

3. Fine grained variables for energy consumption script generation

To integrate fine-grained energy consumption variables and system behavior into a SUMO simulation, we developed two Python scripts for integration. These scripts enhance the simulation by providing detailed insight into the system's operation:

1. System characterization script:

This script introduces various system parameters, including arch length, number and length of stops, number of pedestrians using public transport, bus capacity, time spent at stops, and defines bus and vehicle routes. It also considers the number of vehicles per hour in both scenarios. The script runs the simulation and generates a CSV file containing valuable data. This data includes information such as unique IDs for bus and vehicle routes, the final speed of each vehicle at each simulation step and the number of passengers on each bus.

2. Characterization the system introducing Energy Consumption Estimation Script:

This script extends the simulation to include additional variables that are critical for estimating energy consumption. These variables include rim radius, tire height, rim weight, tire weight, vehicle weight, initial and final speed, number of tires, gravitational force, vehicle mass, distance travelled, sine and arc tangent values, road gradient, speed, rolling coefficient, air density, vehicle frontal area and drag coefficient. Using these inputs, the script calculates kinetic energy, rotational energy, energy required to overcome slopes, rolling energy and energy required to overcome drag. Together these calculations provide an estimate of the total energy consumed during the simulation.

These scripts integrate seamlessly with the SUMO simulation using five key conceptual abstractions, each defining a specific aspect of the system's operation.

3.1 Simulation conceptual abstractions

The simulation abstractions [37] provide a comprehensive conceptual framework for modelling the behaviour of trucks and passengers. Within this framework, the arc conceptual model is used to measure parameters such as length and travel speed.

Another facet of this framework is the nodes conceptual model, which considers signalised and unsignalized nodes and allows the calculation of delay and time spent at these points. In addition, a stop conceptual model has been developed, which is particularly relevant in developing countries where the number of formal and informal stops, their spacing and passenger occupancy play a crucial role in determining bus weight.

Finally, the energy consumption model includes several variables related to the energy consumption of buses. It includes scripts for system characterisation and estimation of energy consumption, making it a comprehensive tool for analysing energy-related aspects of the system.

Each abstraction provides the following aspect of the system's operation.

1. General Abstraction: Provides an overarching framework for incorporating fine-grained energy consumption variables and system behavior.
2. Arches abstraction: Characterizes the physical properties of arcs, including their length and placement within the simulation.
3. Nodes Abstraction: Defines nodes within the simulation, such as intersections and junctions, that affect vehicle flow and routing.
4. Stops abstraction: Models the behavior and characteristics of stops, including the duration of vehicle stops and the boarding and alighting of passengers.
5. Energy Consumption Models Abstraction: Specifies the mathematical models and equations used to estimate energy consumption based on the extensive list of input variables.

By implementing these scripts and abstractions, the SUMO simulation becomes a powerful tool for analyzing and optimizing energy consumption within the simulated system.

3.2 System characterization script

The development of the system characterization script for SUMO involves several steps (Fig. 1):

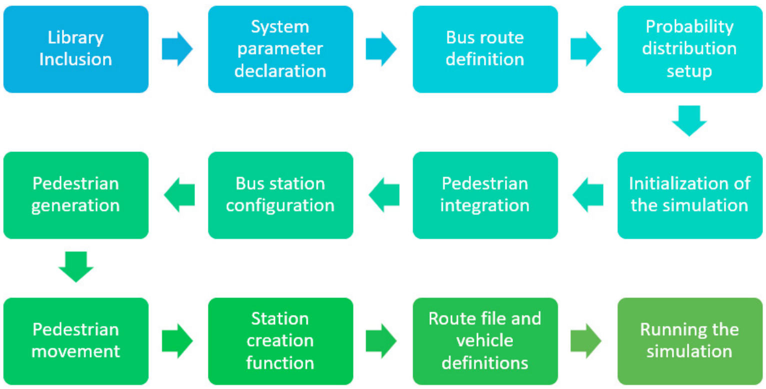

Fig. 1. System characterization steps

1. Library Inclusion: The script begins by importing the necessary libraries required for SUMO's functionality.
2. System parameter declaration: Essential system parameters such as arch lengths, the number, and dimensions of stations per arch, and the number of inhabitants to be transported are defined. These variables can be dynamically adjusted by the user through the script.
3. Bus route definition: Bus routes are defined and assigned their respective IDs, e.g., lines 0b and 1b.
4. Probability distribution setup: The script configures factorials and Poisson distributions. In particular, the Poisson distribution contains an "if" clause that sets values to 0 if they are less than 12. This distribution is used to calculate the arrivals and departures of pedestrians at stops.
5. Initialization of the simulation: The script specifies the start of the simulation, starting at time step 0. It also creates a CSV file to record the results of the simulation, including simulation time, initial and final speeds, and passenger boarding data for the buses.

6. Pedestrian integration: Pedestrians are introduced into the simulation by evaluating each bend to determine if pedestrian traffic is allowed. A list of arcs that allow pedestrian traffic is generated.
7. Bus station configuration: The script defines the location and number of bus stops in the simulation.
8. Pedestrian generation: Pedestrians are generated at 5-minute intervals, this time period is user configurable. If the time interval is exact (resulting in "st" being 0), the script calculates the Poisson distribution to determine the proportion of pedestrians to generate during that period. If the number of pedestrians exiting in those 5 minutes is less than the value predicted by the distribution, pedestrians will exit randomly and be positioned at random locations within the permitted arcs.
9. Pedestrian movement: Once created, pedestrians are directed to random stops (modifiable to the nearest stops). If the desired stop is on line 0b, the pedestrians board the bus, otherwise they board the other line. All pedestrians disembark from the bus at the terminal (with the option of modifying stations using distributions).
10. Station creation function: The script defines a function to create stations for each arc. It subtracts the length of the station from the length of the arc and divides it by the number of stations to be created. An additional file with the extension .add.xml is created to declare the stops using a template text file containing stops without IDs and the lanes in which the lines run. A loop uses this template to generate the stops. The starting point of the first stop is determined as the length of the stop minus a margin before the end of the block, as stops are not placed at corners, and the end of a stop is the start of the next stop, stop + stop length, to generate the additional file.
11. Route file and vehicle definitions: The script specifies various parameters, including bus capacities, bus flows in both directions, vehicle types (bus), bus stop durations, truck routes and flows of both trucks and vehicles in general. This information is used to create the route file (.rou.xml).
12. Running the simulation: Finally, the program is executed, and options are verified based on defined parameters. It generates vehicle routes, initiates the simulation in SUMO with traci as the server and produces the results in a CSV file.

This comprehensive script allows for flexible characterization and operation of a SUMO simulation, accommodating user-defined parameters for in-depth study and analysis of traffic and transport systems.

3.2 Energy consumption estimation script

The energy estimation script has been developed through the following steps. First, the script opens the results CSV file. It then defines a function called 'total_energy' which contains all the variables needed to estimate the energy.

Next, the initial and final velocities are converted to metres per second (m/s) and the kinetic energy required for the motion is calculated. Rotational energy is determined using parameters such as rim radius, tyre height, rim weight, tyre weight, number of tyres and moment of inertia.

To calculate the energy required to climb a slope, the script takes into account factors such as gravity, vehicle mass, distance, sine, arc tangent and slope variables. Rolling energy is based on the rolling coefficient, vehicle weight and distance travelled. Finally, the energy required to overcome air resistance is estimated by taking into account air density, vehicle frontal area, drag coefficient, speeds and distance travelled.

The total energy required is calculated by summing all these previously calculated energy components. In addition, an "if" clause is introduced to check that the initial and final speeds are the same. If the speeds are different, the script returns the total energy, otherwise it returns "0".

Finally, the imported data array from the CSV file serves as input values for the variables, allowing the script to estimate the energy consumption for each simulation step and in an aggregated manner.

4. Scripts application example

The scripts developed were implemented within a SUMO simulation environment, using a network created using netedit. This network consists of 31 segments, each 100 metres long.

To evaluate the performance of these scripts and to compare energy consumption estimates under different conditions, two different scenarios have been developed. In scenario one there are two bus stops along each segment, while in scenario two there are four bus stops per segment.

Each scenario includes five different routes, one of which is for buses. These buses have a capacity of 55 passengers and each stop has a duration of 30 seconds. There is also a constant bus flow of 35 buses per hour in both right and left directions, resulting in a vehicle flow of 900 vehicles per hour. There is also a pedestrian flow of 1800 people per hour and the bus stops are 10 metres long.

All elements, including bus stops, buses, vehicles, passengers, routes and CSV format data files, are dynamically generated by a Python script. The execution of this Python script produces six files: an additional XML file, a route XML file, a journey information XML file, two bus stop TXT files, and a CSV file containing the data (see Fig. 2).

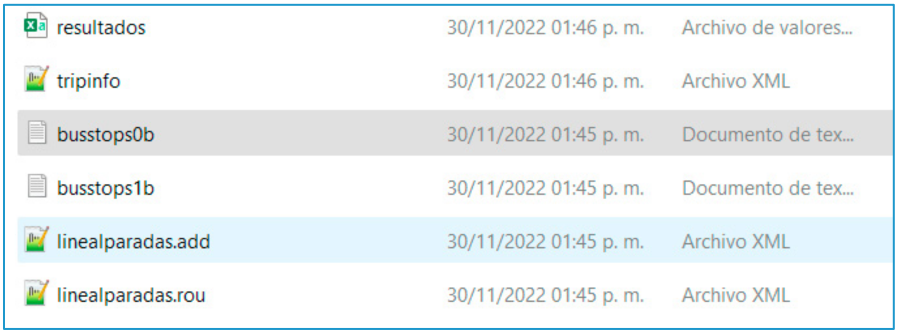

Fig. 2. Files generated through system characterization python script.

The data processing process involves the analysis of a results CSV file, where the objective is to organise the bus flows, determine their initial speeds at each step, and calculate the total vehicle weight, considering the weight of the passengers (average 70 kg in Mexico City) at each simulation step. An energy consumption estimation script is then run and the results of both scenarios are compared.

The results of these scenarios show that it's crucial to note that the energy consumption estimates presented in this study only consider the initial and final speeds and the weight of the vehicles at each simulation step for energy consumption estimation. However, several other variables such as rim radius, tyre height, rim weight, tyre weight, number of tyres, gravity, vehicle mass, distance, sine, arc tangent, slope, rolling coefficient, air density, vehicle frontal area and drag coefficient are currently included in the script. However, they have not been included in the estimates presented as the data is still being collected for potential application in a case study in Mexico City.

The results of both simulations underline the significant impact of stop spacing on energy consumption. The introduction of four additional stops with reduced spacing results in a 25.3% increase in energy consumption, equivalent to 289,096,280 Joules (as shown in Table 1 and Fig. 3).Therefore, the script does provide a comprehensive energy consumption calculation and the proves that not major improvements are needed to impact and reduce energy consumption.

It is then recognised that a new script is needed, one that can identify the lengths of arcs within a network to define the placement of stops in each arc. This script is based on network information and the demand flow of both cars and buses within the network.

Table 1. Energy consumption comparison

Stops/energy consumption	Energy consumption (Joules)	Increase
Four stops	1,432,429,581.57	-------------
Two stops	1,143,333,301.56	25.3%
Difference	289,096,280.00	

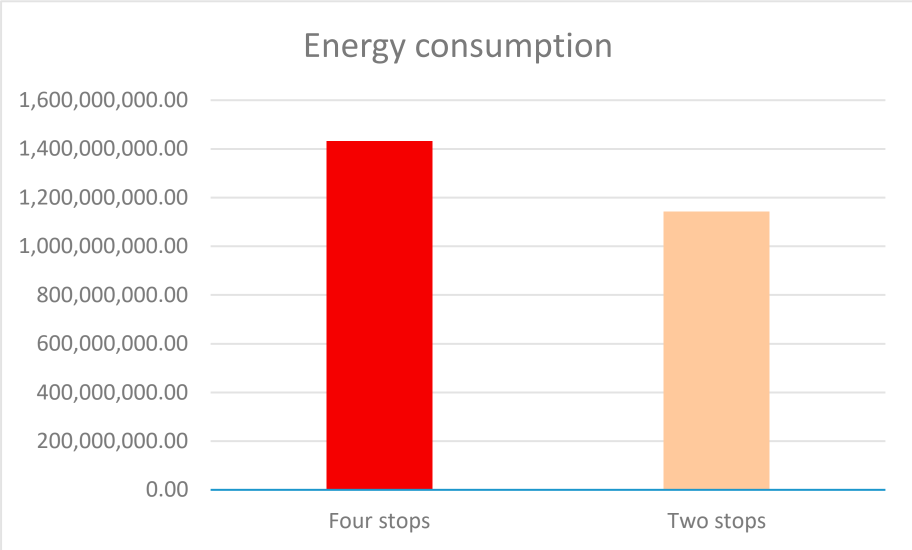

Fig. 3. Energy consumption comparison

5. Conclusions

The use of simulations to estimate energy consumption and suggest feasible improvements that can effectively impact energy consumption is essential. However, existing simulation models in this area often lack the fine-grained variables required for accurate calculations. It's therefore crucial to incorporate and characterise these variables in order to truly measure and improve energy consumption. This need is particularly acute in developing countries, where the characteristics of public transport are very different from those in developed countries.

The first draft of Python scripts presented here aims to introduce fine-grained energy consumption variables into a public transport simulation using SUMO. These scripts show promise for modifying system characteristics and improving energy consumption estimates. However, they require further refinement and the addition of variables not currently included in the simulation needs to be validated.

These scripts are valuable for creating a simulation that not only focuses on operational changes, but also considers their impact on energy consumption. We are also considering adding emission estimates to the Python scripts, as energy consumption has a direct impact on the emissions generated by public transport.

As part of future work, we plan to extend the presented scripts and apply them to a case study in Mexico City. This will allow us to propose measures to reduce energy consumption and emissions. In addition, we are considering incorporating cost-related data into the simulation. These scripts and the conceptual abstractions of the model will serve as a basis for further integration and development of intelligent transport systems and simulation-based digital twins.

In summary, as future work will include incorporating the energy consumption model, developing an emissions estimation script, and extending the simulation to consider time requirements at stops and stop spacing based on demand patterns. This comprehensive simulation will be carried out as part of a case study in Mexico City.

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