Transport optimization heuristic approach to decrease the Vehicle Miles Traveled and CO2 emissions: A case of School Bus Routing Problem

Dejan Dragan,
Associate Professor, University of Maribor, Slovenia

Tomaž Kramberger,
University of Maribor, Slovenia

Klemen Prah,
Assistant Professor, University of Maribor Slovenia

Maja Rosi
Teaching Assistant, University of Maribor, Slovenia

Abstract

The transport sector generates about 14% of global greenhouse gas (GHG) emissions and about 25% of GHG emissions in the EU. Contrary to other relevant economic sectors, emissions produced by transport are still growing. The need for rapid reduction of GHG emissions, particularly those related to CO2, has become imperative.. To achieve this objective, several approaches were adopted such as alternative technologies, sustainable community changes, or changes in driving behavior might be the future solutions. Another possible approach is to reduce the vehicle miles of traveled (VMT). The paper addresses the concept of VMT reduction, based on transport optimization approach and 3D GIS technology. The proposed approach has been tested for the case of School Bus Routing Problem (SBRP). The paper discusses working framework of the applied optimization algorithms. For computation of the CO2 emission, two different approaches have been used. The algorithm for playing different scenarios for average fuel consumption of vehicles of transport fleet has also been developed for the optimized case. The results show that the optimization of bus stops, vehicle routes and driving schedules can significantly reduce the VMT and consequently also the corresponding CO2 emissions.

Keywords

Transport optimization;Heuristic approach;Vehicle Miles Traveled;CO2 emissions; School Bus Routing Problem; Three-dimensional (3D) Geographic Information Systems.

Introduction

*E*nergy is one of the priorities in the world today. Significant work is being already done on the ways to improve energy production and to address many possible solutions to this global issue. Environmental degradation, coupled with various economic and social problems, has led many nations to start producing energy through resources such as sunlight, wind, waves, geothermal energy, water etc. Non-renewable energy sources are still considered as a traditional way of producing energy, but the governments around the world are actively trying to increase the share of clean energy production to reduce existing thermal power plants, which largely contribute to the CO2 emissions into the atmosphere. Fossil fuels are the primary source of electricity production today. Unfortunately, fossil fuels are also major pollutants of the environment. The burning of fossil fuels releases substantial amounts of CO2, which is one of the gases that contribute most to climate change in the form of creating a so-called greenhouse effect and global warming.

The global emissions

The global greenhouse gas (GHG) emissions have grown up significantly since the pre-industrial era estimated an increase of 70% between the years 1970 and 2004 (Le Quéré et al., 2018; Metz et al., 2007). The human activities are also guilty for such a massive increase of GHGs emissions and a detected intensification in atmospheric GHG concentrations. The distributions of global GHG emissions concerning the type of gas and concerning the economic activities are shown for the year 2010 (EPA, 2019)and for the year 2004(EPA, 2014) in Figure 1 & 2 respectively as below:

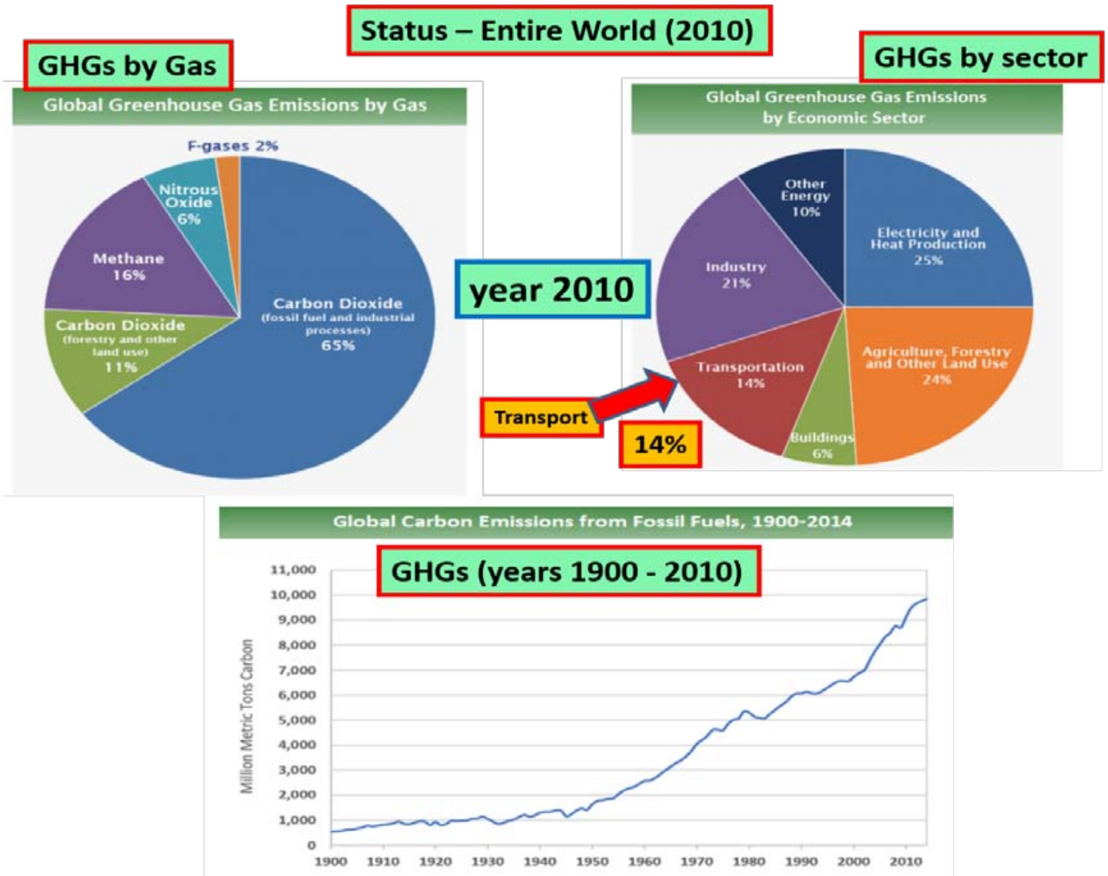


Figure 1: The distribution of global GHG emissions concerning the type of gas and economic activities (for the year 2010)

As can be seen from figures 1 and 2, the transportation sector is one of the massive generators of GHG emissions (about 14% in 2010 and 13.1% in 2004). Moreover, it is detected as one of the few economic sectors, where the emissions are still mounting(Chapman, 2007). Hence, objectives about reducing the GHG emissions generated by the transport, particularly those related to CO2, are on the top list of priorities all over the world.

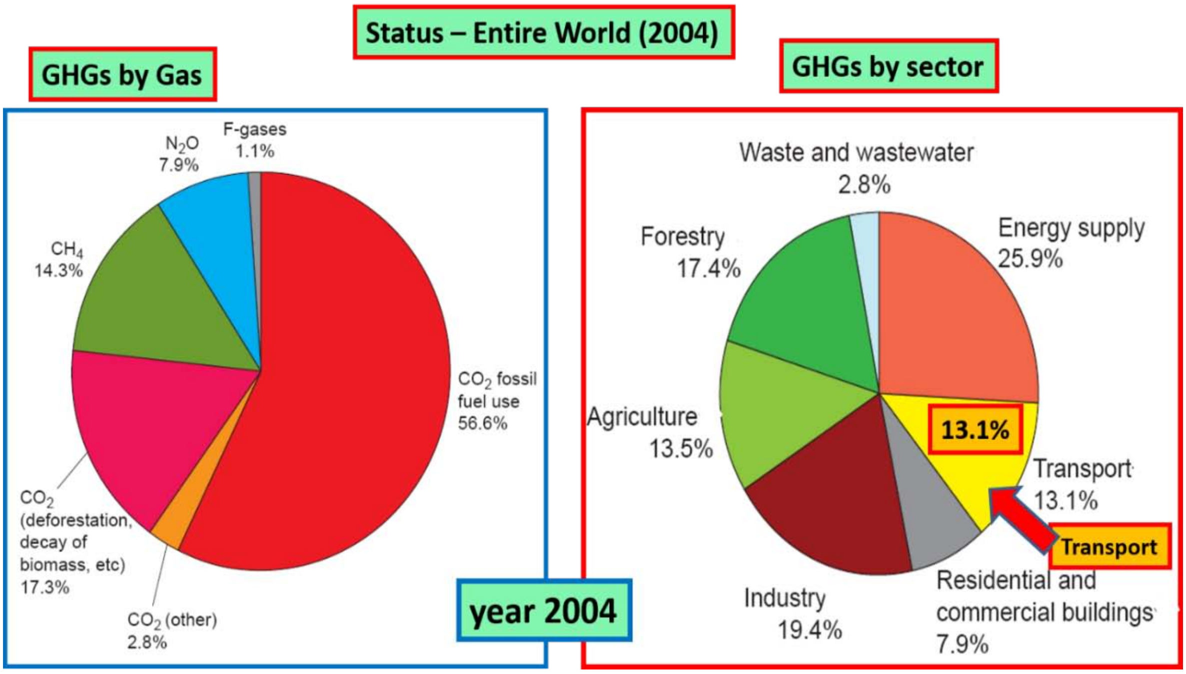


Figure 2: The distribution of global GHG emissions concerning the type of gas and economic activities (for the year 2004)

A range of policies, related to climate change, energy security, and sustainable development, have been conducted for different economic sectors in many countries to efficiently respond to the phenomena of escalation of global GHG emissions. Unfortunately, these measures are still not large enough to counteract the global increase in GHG emissions. With current policies about climate change mitigation, the global emissions will continue to grow in the next few decades (Le Quéré et al., 2018; Metz et al., 2007).

The emissions in the European Union

Regarding the European Union, the comparison of the distribution of GHG emissions (for years 1990 and 2017) with respect to the type of economic sector is shown in figure 3 (EEA, 2019b). As it can be seen the transport sector was responsible for around a 25% of GHG emissions in 2017 meaning that it is the second principal generator of emissions, immediately after the fuel combustion and fugitive emissions from fuels (without transport – about 54%). Even more worrying fact is that the increase for 10% of transport emissions happened in just 27 years (from 15% in 1990 to 25% in 2017) (EEA, 2019b).The emissions generated by transport are still growing in the EU, similarly as in the global case (the entire world) and 5)(ECCA, 2014; EEA, 2019a, 2019c). The emissions from other economic sectors have on average decreased for about 10% between years 1990 and 2008and more than 20% between years 1990 and 2017 (ECCA, 2014; EEA, 2019a, 2019c). The emissions related to the transport sector have significantly increased in the same period, as can be seen from the rising trends of all types of transport as shown in figure 4.

The paper addresses the conception of VMT reduction, based on transport optimization approach and 3D GIS technology.

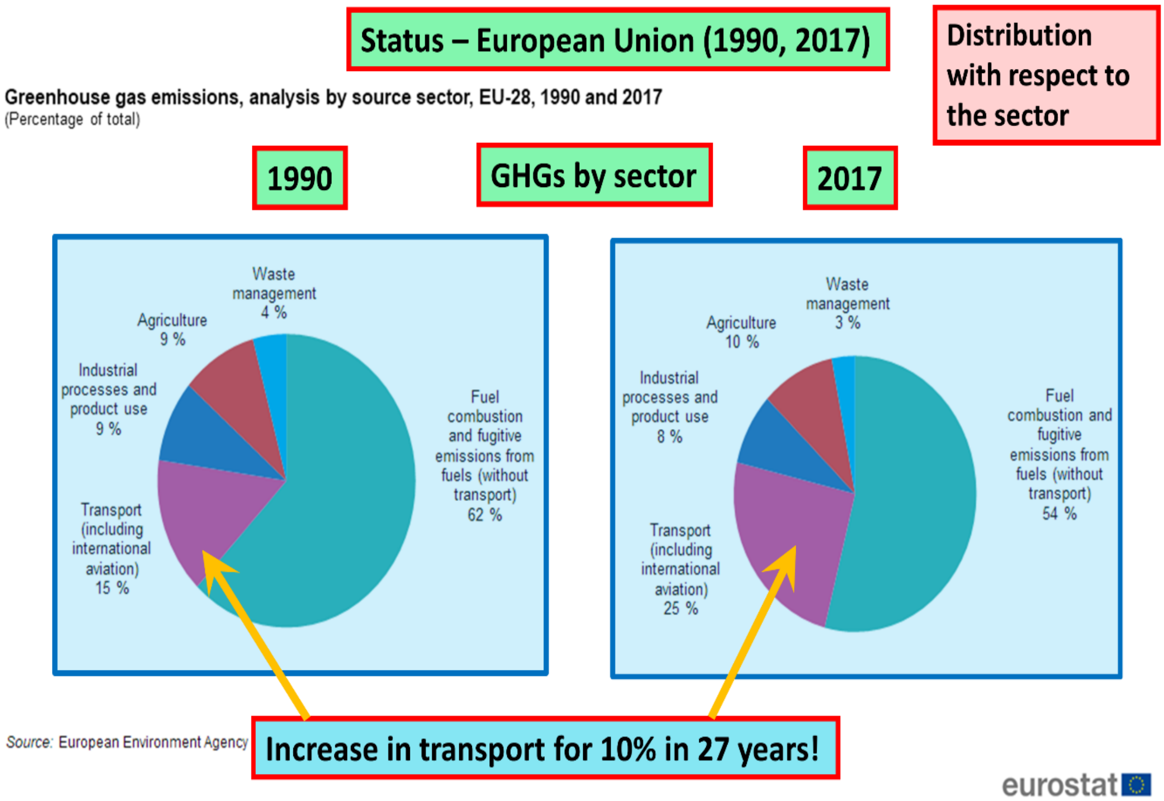


Figure 3: The comparison of the distribution of GHG emissions (for years 1990 and 2017) with respect to the type of economic sector

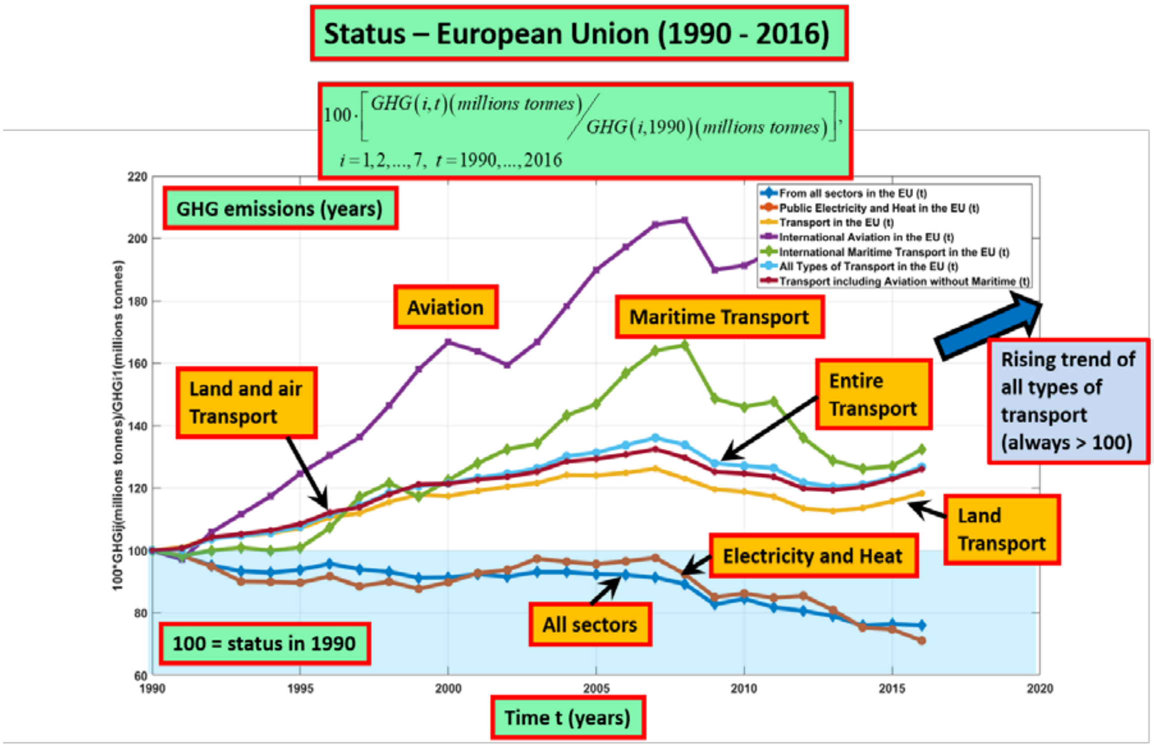


Figure 4: The normed time series of GHG emissions (between years 1990 and 2017) with respect to the type of economic sector (different kinds of transport, all sectors, electricity, and heat).

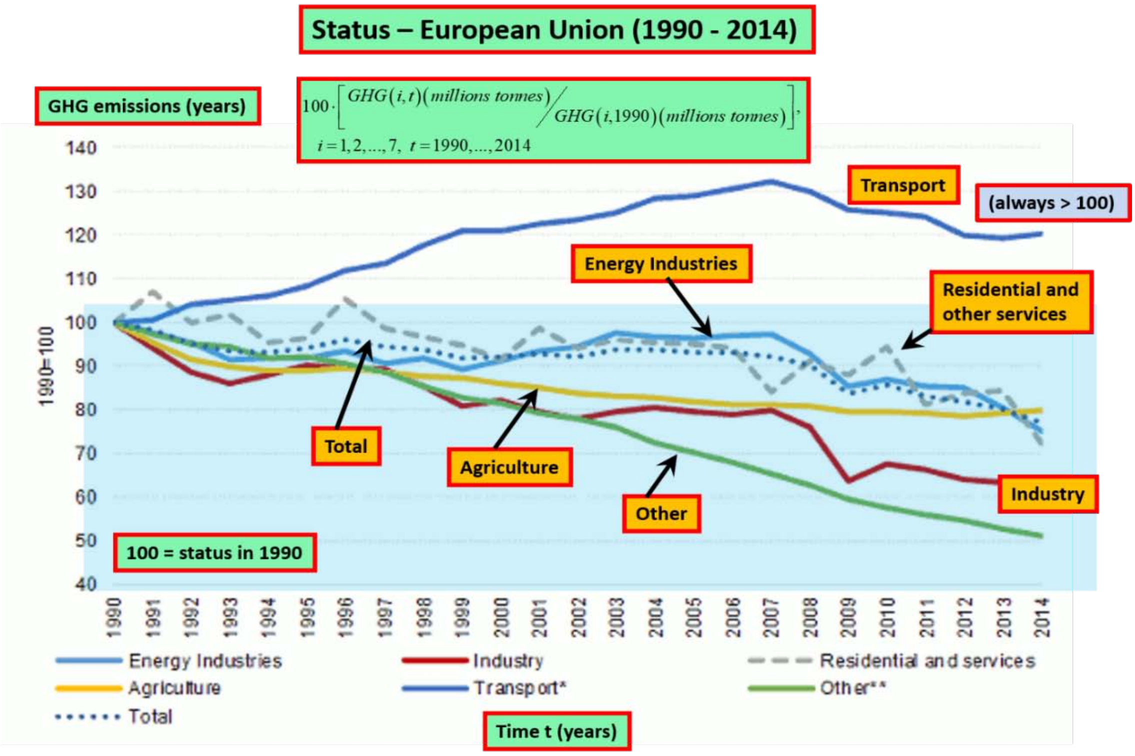


Figure 5: The normed time series of GHG emissions (between years 1990 and 2014) with respect to the type of economic sector.

Figure 6 shows the distribution of GHG emissions in the EU transport sector regarding the mode of transport for the year 2007(ECCA, 2014). It can be seen that about 68% of those emissions are related to road transport. The latter has significantly increased in the time period from 1990 to 2007 since a personal and freight transport had enormously increased.

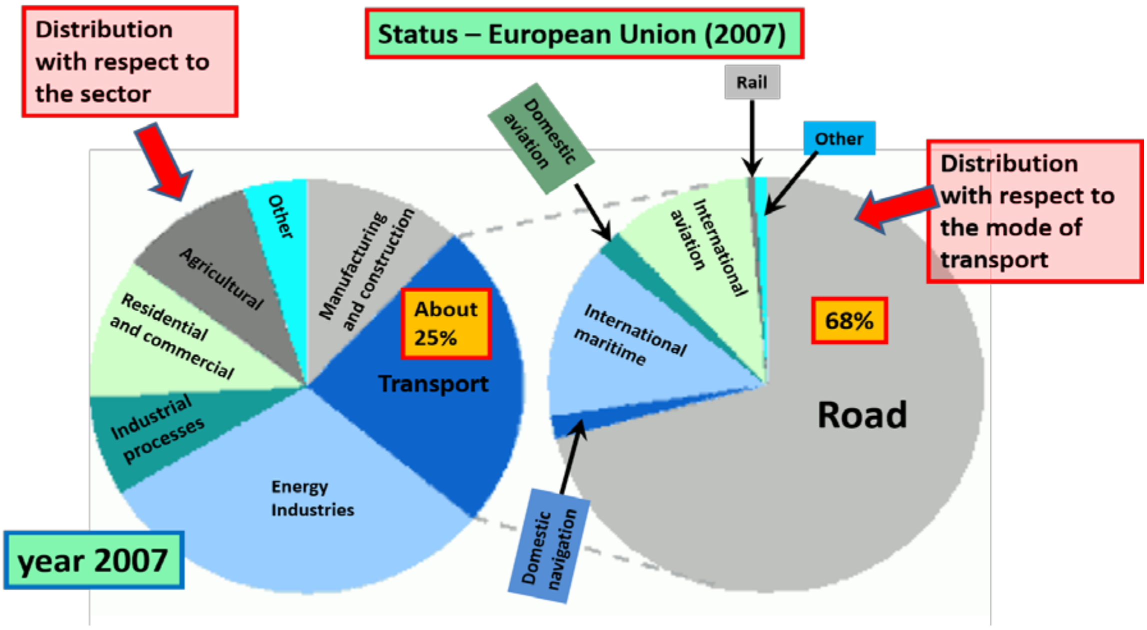


Figure 6: The distribution of GHG emissions in the EU transport sector regarding the mode of transport for the year 2007

The proposed optimization framework for solving the SBRP problem and estimating the CO2 emissions

This work is focused on the reduction of CO2 emissions, which are the consequence of road transport. The work represents a continuation of the research, whose earlier stages were presented in severalprevious papers of the authors of the present paper (e.g., (Dragan et al., 2011; Dragan et al., 2012; Kramberger et al., 2013)). Our approach is grounded on the optimization of road transport to reduce the "*Vehicle Miles Traveled*" (VMT), which might in principle also cause the reduction of CO2 emissions. The approach uses diverse heuristic techniques, which are conducted via several stages. The application of *three-dimensional Geographical Information System* (3D GIS) is also used, which enables the framework with 3D geographical data for the purpose of various management and analysis tasks on these data (Heywood et al., 2011).

In order to demonstrate, how the reduction of VMT, based on optimization, can also lead to a significant reduction of CO2 emissions, the case study of the well-known *School Bus Routing Problem* (SBRP) (Park and Kim, 2010) has been applied and conducted for one Slovenian municipality, named the *Municipality of Laško*(from here on *MOL*). In this study, the optimal allocation of bus stops (BS) was applied as a first step. Then the optimal driving routes, the optimal driving fleet and the optimal driving schedules were calculated. In the next step, the calculation of VMT for the non-optimized and for the optimized situation was done. Also, the CO2 emissions in both situations were estimated by means of two different approaches:the *Emissions' Factor Method (EFM)* and the *Fuel Consumption Method (FCM)*)(Anable et al., 1997). In the final stage, the algorithm for playing the different scenarios for average fuel consumption of vehicles of the transport fleet was developed and conducted for the optimized situationby employing the FCM method. Since the algorithms for optimal allocation of bus stops and determination of optimal optimal driving routes, driving fleet and driving schedules have been already more in-depth presented in our previous reports (see (Dragan et al., 2011; Dragan et al., 2012; Dragan et al., 2016; Kramberger et al., 2013)), the major emphasis of this paper is dedicated to the aforementioned calculations of CO2 emissions.

The simulated results show that the optimization of BS, vehicle routes and driving schedules can significantly reduce the VMT and consequently, the corresponding CO2 emissions if compared to the un-optimized situation.Even more, the comparison of estimated optimized results of all scenarios with the non-optimized situation has confirmed the promising performance of the developed mechanism and convinced us that the VMT reduction, based on the optimization, can truly contribute to the significant decrease of the CO2 emissions.

Surprisingly, the insufficient attention has been dedicated so far to the VMT reduction based on transport optimization, as it was detected by means of careful examination of the existing literature (Kramberger et al., 2013). Since the identified gap is relatively big, we believe that this work might have represented some contribution to the addressed scientific field. Furthermore, at least to our best knowledge,we have also discovered that the developed algorithm for playing the different scenarios for vehicles' average fuel consumption might have represented another unique contribution that could not be found in the existing literature.Also, except some of our previous research (Prah, Keshavarzsaleh, et al., 2018; Prah, Kramberger, et al., 2018), there have not been many similar reports detected that address an optimization based on 3D GIS data. Finally, from a practical point of view, the entire optimization mechanism as a part of a decision support system is successfully running in theobserved municipality for several years already, while the cost savings can be measured in hundreds and hundreds of thousands of Euros.

LITERATURE REVIEW

The measures to reduce the GHG emissions in the EU transport sector

Since the GHG emissions (especially those from CO2) from the road transport are by far the most problematic, the EU governments have become focused to adopt a serious emission reduction measures, particularly for the road transport(EC, 2000; EPA, 2011). From figure 7 it can be seen that state authorities at different levels have adopted a whole set of regulations, strategies, policies, andmeasures to reduce the road emissions. More in-depth details about explaining the strategies and policies in figure 7 can be found in (Dragan et al., 2016; Kramberger et al., 2013).

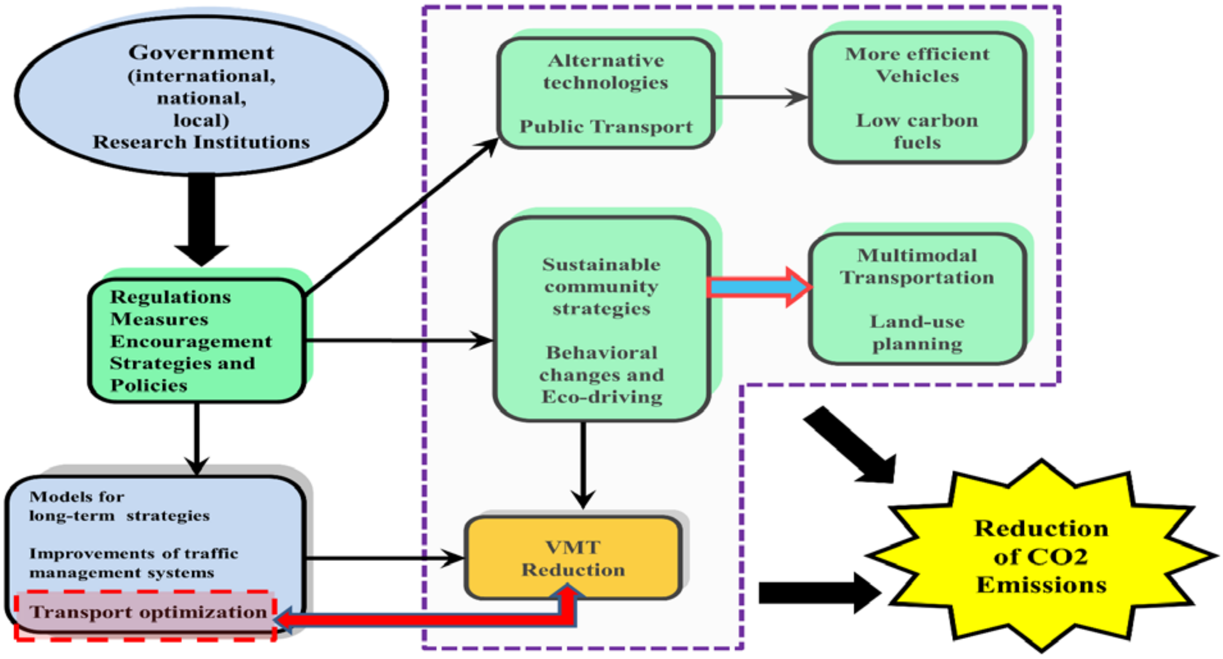


Figure 7: An overview of some measures, which have been adopted in the EU for reducing the CO2 emissions related to road transport (the emphasis of this research is on the transport optimization)

In general, the following strategies, regulations, and policies are pushed by the governments (Barth and Boriboonsomsin, 2014; Difiglio, 1997; Dragan et al., 2016; Heres-Del-Valle and Niemeier, 2011; Kramberger et al., 2013; Moore et al., 2010):

- *The use of alternative technologies* (more efficient vehicles, low carbon fuels, etc.),
- *The adoption of sustainable community strategies* (integrated multimodal transportation, land use planning, etc.)
- *The increased use of public transport*,
- *The behavioral changes in the driving patterns*,
- *The increased application of so-called eco-driving*, and so on.

Besides the aforementioned approaches, the VMT reduction is also targeted. (Chapman, 2007; Difiglio and Fulton, 2000; Heres-Del-Valle and Niemeier, 2011). However, the VMT reduction essentially depends on the change in human behavior and travel patterns in the sense of increasing the use of public transport and simultaneously reducing the car travel (Moore et al., 2010). Furthermore, the VMT reduction also relies on long-term strategies, which are established according to the computer models for simulation of the impacts of presumed behavior, or land-use changes, on the VMT. Naturally, the reliance only on these computer models can lead to quite uncertain conclusions(Heres-Del-Valle and Niemeier, 2011).

Radical changes in human behavior would be needed to reduce the VMT and related CO2 emissions in road transport to the desired level. On the other hand, the subtle improvements in traffic management systems and optimization of road transport might have been adopted to considerably reduce the VMT and CO2 (see shadowed block “Transport optimization” in figure 7, which manifests our approach).

The reduction of the VMT and CO2, and relation to the SBRP problem

Many authors, e.g.,(Desrosiers, 1986; Ellegood et al., 2019; Rita M. Newton and Thomas, 1969; Rita M Newton and Thomas, 1974; Park and Kim, 2010; Schittekat et al., 2006)have studied the SBRP problem. A jointline of these papers is the fact that the optimization in principle reduces the VMT and henceforth also the transportation costs. Moreover, we can also suppose that the reduction of VMT reduces GHG emissions as well. It is true that according to the opinion of (Moore et al., 2010), the climate change policy should concentrate directly on reducing the GHG emissions, rather than through the use of the instrument of VMT reduction.

However, on the other hand, our research investigates the optimization-based VMT reduction, where the context of the environmental point of view is not excluded. By other words, our attention is focused on the studying of the relations between the reduction of the VMT and the probable reduction of CO2 emissions, where we are alsopredominantly interested in the level of the drop in CO2 emissions.

The SBRP problem as a hard six-step heuristic-based combinatorial optimization problem

The SBRP problem usually does not cover only the optimization of school bus routing, but also some other essential steps, like the bus stops’allocation, the identification of eligible pupil commuters, the road network design, the planning of the starting and ending time of lessons, etc. Generally, the SBRP can be divided into sixminor sub-problems as shown in figure 8 (Desrosiers, 1986).

The scholars usually do not address all the SBRP sub-problems simultaneously, since the level of complexity is quite high. Although the SBRP itself embodies the unique classical optimization problem, its sub-problems can be classified as diversevariations of other typical optimization problems. For example, the sub-problem of the school vehicles’routing is very similar to the *Vehicle Routing Problem* (VRP), while the mixture of sub-problems 2 and 3 (i.e., the allocation of BS and construction of vehicle routes) can be classified into the cluster of *Location-Routing Problems* (LRP) (Park and Kim, 2010).

In solving the SBRP, we have to find an optimal schedule for school vehicles’ fleet, where every vehicle picks up the pupils at the BS and then delivers them to their schools. During the SBRPsolving process, the whole variety of different constraints must be usually fulfilled, such as the maximum riding time of individual pupil in a vehicle, thetime window of schools, the maximum capacity of vehicles, etc.(Desrosiers, 1986; Park and Kim, 2010).

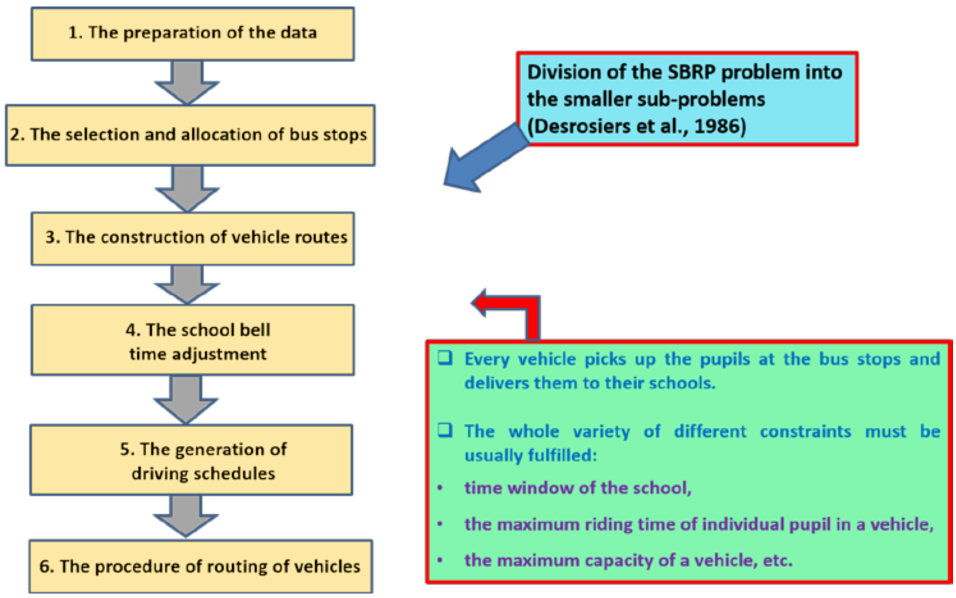


Figure 8: The SBRP problem as a hard six-step heuristic-based combinatorial optimization problem

In general, in most cases, we are confronted with challenging problems when we are trying to solve the SBRP problems. Consequently, the use of more sophisticated heuristic approaches is mostlynecessary. In the last two decades, there have been many heuristic procedures presented for the solving of SBRP problems, such as tabu search algorithms, genetic algorithms,simulated annealing, deterministic annealing, and many more. Further details about these algorithms can be investigated in works(Dragan et al., 2019; Ellegood et al., 2019; Park and Kim, 2010).

THE SBRP PROBLEM IN THE ADDRESSED MUNICIPALITY OF LAŠKO

In Slovenia, the school traffic systems are typically organized by the municipalities and not by the individual schools. Moreover, vehicles for school transport are frequently shared by multiple schools. Consequently, the adjustment of schools' opening and closing times is ordinarily required, and the scheduling of vehicles for multiple schools is often necessary as well.

The case study addresses the use of (8+1) passenger vans, which are possessed by the municipality. These vehicles are on average relatively “obsolete” since the municipality budget is after the economic crisis in a somewhat problematic financial situation. The MOL is positioned in Central Slovenia and has the sub-alpine hills, while the flat land is spreading along the river Savinja and its tributaries. The municipality has a quite high population density ($69\,inhabitants/km^2 \ldots year\ 2009$)if compared with the Slovenian average ($101\,inhabitants/km^2 \ldots year\ 2009$). The municipal road networks are one of the most diverse in the country, which means: $^{30\ m\ of\ roads}/_{citizen}$, while the Slovenian average is: $^{7\ m}/_{citizen}$ (Horvat, 2006). The complex terrain, a large number of settlements and individual road segments, inadequate levels of maintenance and poor quality of construction, are the cause of fairly big deterioration of local roads (Horvat, 2006).

The real data for manifestation in this study were used for the school year 2009-2010, which has been the last year with a none-optimized situation. At this time, the municipality has had the commitment to provide the services to circa 562 pupils, who had been located at different addresses, while the total sum of road distances had been 960 km of roads in this area (c.f. figure 9). The transport routes were not well organized since the vehicles have had to travel a lot of non-necessary additional kilometers. Moreover, the vehicles were usually not fully loaded, while the routes had been sometimes doubled or even tripled (Dragan et al., 2011).In order to remove these deficiencies, the optimization of pupils' transport had to be applied. The latter had taken into consideration the design of optimal BS locations, bus routes, and driving schedules.

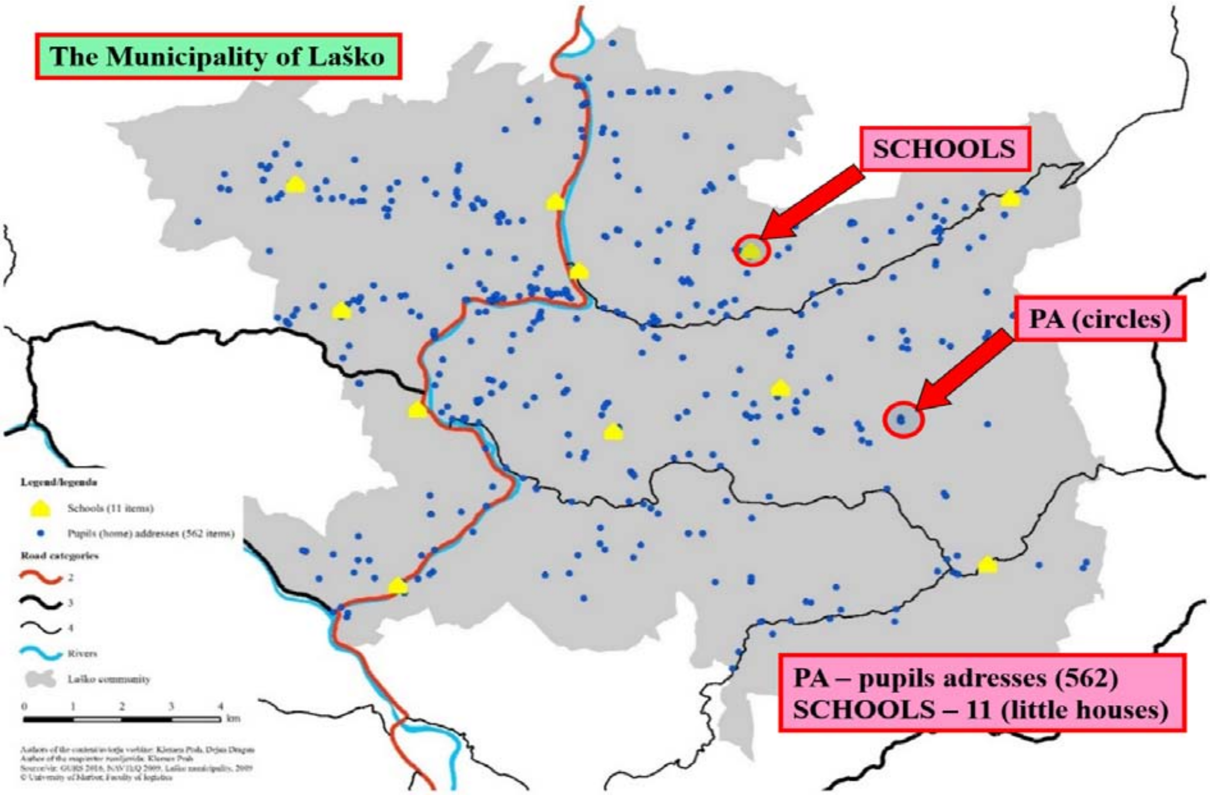


Figure 9: The locations of 11 schools (little houses) and the addresses of 562 pupils (little circles - points) in the MOL (for the last "unoptimized" school year 2009-2010)

THE CONCEPTUAL FRAMEWORK OF THE HEURISTIC OPTIMIZATION PROCEDURE AND THE CONTEXT OF THE ENTIRE RESEARCH

The conceptual framework of the designed heuristic optimization procedure

In this section, the conceptual framework of the heuristic optimization procedure, which was applied to solve the SBRP problem in the observed municipality, is introduced(c.f. figure

10). As it can be seen in figure 10, the characteristics of the road network, the bus stops' candidates data points, and the residential addresses of the pupils must be injected as the main inputs into the optimization process. The road data point shave been generated using 300 meters' segmentation of the road network by means of GIS technology, according to the recommendation of the observed MOL. After the initial setup, the four-stage optimization procedure that comprises four algorithms had been executed (see figure 10). Thus, the main problem has been divided into four sub-problems, which were processed one after another.

During the first stage (**ALGORITHM 1**), the initial roads data have been reduced to decrease the potential candidate road points for optimal BS to an acceptable level; otherwise, the serious computational problems might have appeared.

During the second stage (**ALGORITHM 2**), the Monte Carlo simulation-based optimization method has been deployed to determine the optimal number and optimal location of bus stops based on the further reduced set of candidate road points (Dragan et al., 2011).

During the third stage (**ALGORITHM 3**), the optimal bus routes, driving schedules and driving fleet have been calculated using the well-known Arc Logistics software and ArcGIS extension Network Analysis(ESRI ArcGIS) (Dragan et al., 2012; Prasertsri and Kilmer, 2003; Weigel and Cao, 1999).

Moreover, while executing **ALGORITHM 3**, the estimated CO_2 emissions havealso been calculated based on the calculated VMT for the simulated optimized case (Kramberger et al., 2013). For this purpose, the *Emissions' Factor Method* and the *Fuel Consumption Method* were applied. In the final stage, **ALGORITHM 4** for playing the different scenarios for average fuel consumption of vehicles of the transport fleet was executed for the optimized situation by employing the FCM method.

The final results thus include: the optimal BS, the optimal routes of vehicles, the optimal driving schedules, the optimal driving fleet, and, the amount of VMT and produced CO_2 emissions for every single vehicle and the entire fleet. To convince ourselves that the optimized results truly lead to the lowered values of CO_2 emissions, the comparison between the un-optimized (real) and optimized (simulated) case was also processed.

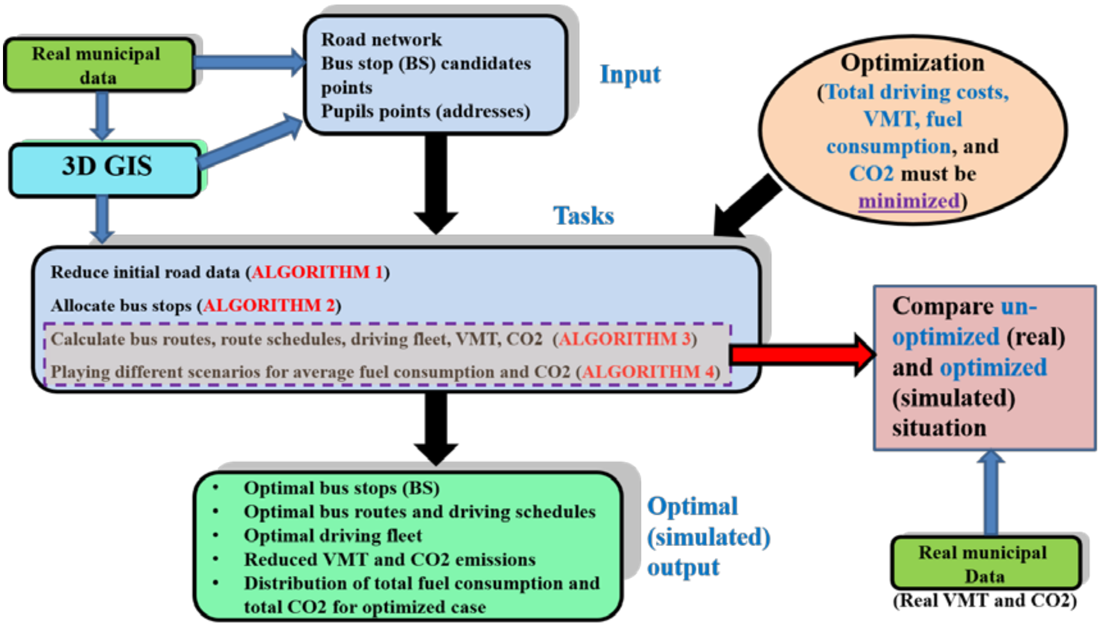


Figure 10: The conceptual framework of the used heuristic optimization procedure

The context of the entire research and relations with the previous studies

The work presented in this paper is a logical continuation of our previous research(Dragan et al., 2019; Dragan et al., 2011; Dragan et al., 2012; Dragan et al., 2016; Kramberger et al., 2013; Prah, Keshavarzsaleh, et al., 2018; Prah, Kramberger, et al., 2018). The evolution of entire research with the time progress is shown in figure 11 (see also figure 10). The framework for solving the basic SBRP problem was established almost ten years ago (block A). At that time, the entire mechanism was also gradually implemented and tested in the observed MOL (block B). The latter included the physical implementation of identified optimal BS with some minor modifications due to terrain and road network characteristics in order to create a realistic bus stops' topology and prevent dangerous situations when pupils are approaching the assigned BS. Also, the drivers of the optimized fleet have received the optimal schedules and routes that must be processed every day. During the transition from un-optimized to the optimized state, the real results under the optimal conditions have more or less confirmed the hypothesized promising simulated optimal results. The latter means that the optimization of the school bus transport had been quite successful in real practice as well, while the related costs and VMT dropped significantly.

Since the situation slightly changes every year due to the arrival of the first-grade pupils and departures of the last-grade pupils, the recalibration of the entire system is needed every year (see block C). The results show that the physical locations of the BS are more or less stable and time-independent due to the mostly unchanged demographical distribution of the population dispersed throughout the municipality.

After the success of the implementation of our system in the Laško municipality, the neighboring municipalities have also become interested in solving their SBRP problems. As a result, the entire SBRP solving system was developed and implemented in the Municipality of Žalec (block D) as well, where the complexity of the problem was even higher (block E) (see (Dragan et al., 2019)). Later on, further research has gone in several different directions, mostly dedicated to the prototypal improvements and modifications of the existing systems (e.g., a deployment of data clustering, transition to 3D GIS – see block F), expansion to the other municipalities (see block D), and research related to the development of different emission models (block H). Moreover, the 2D and 3D GIS results were also compared (block G), while in this paper, the main emphasis is on **ALGORITHM 4**from figure 10 (block I), as a more straightforward competitive framework that can challenge the results of the much more complex modified MEET macroscopic emission model integrated into the Monte Carlo scenario-playing framework (block J) (see (Dragan et al., 2016)).

The methodology to solve the SBRP problem and estimate the CO2 emissions

The main algorithms to solve the SBRP problem

In this section, we only briefly discuss some significant steps of the first three algorithms from figure 10. The last one, i.e., **ALGORITHM 4**, will be more in-depth presented later in this paper. The more in-depth details about earlier versions of these algorithms can be found in some of our previous reports (e.g., (Dragan et al., 2011; Kramberger et al., 2013)).

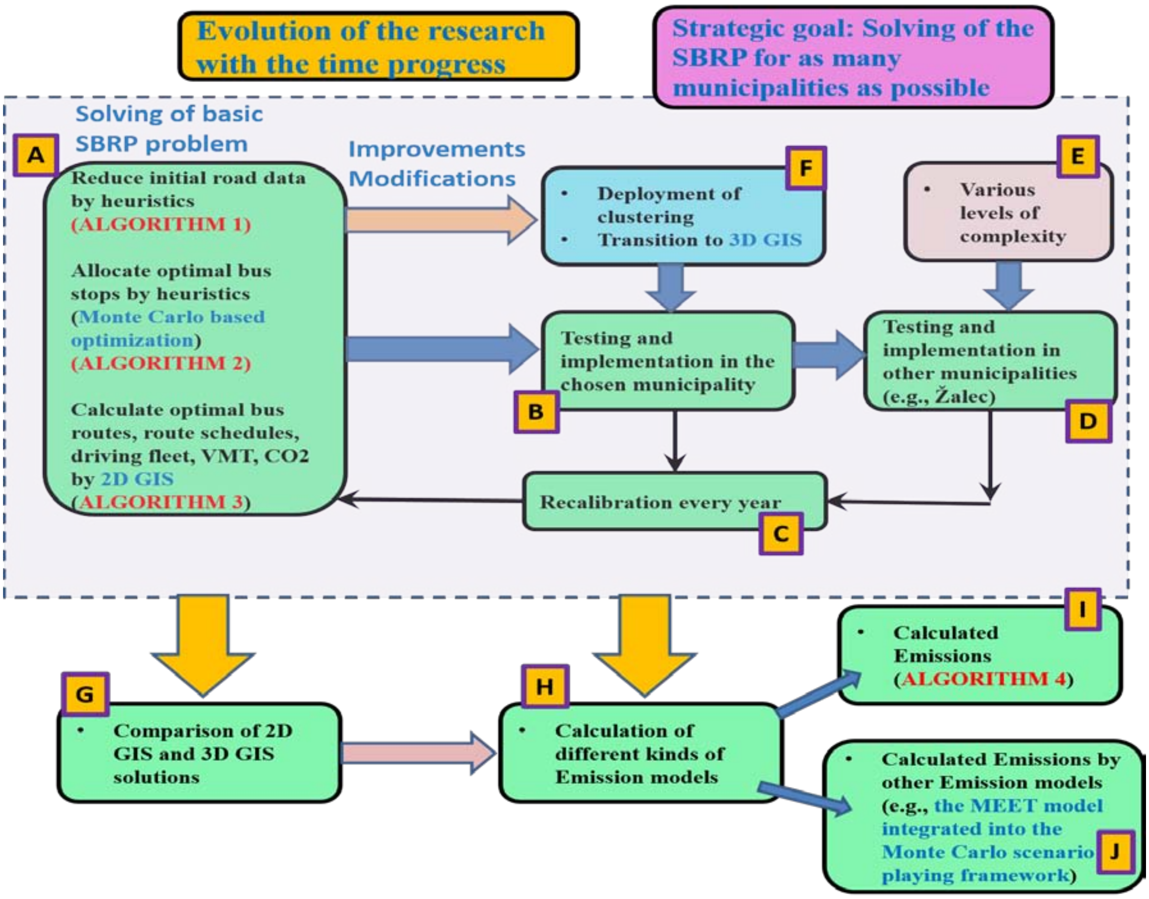


Figure 11: The evolution of entire research with the time progress

The algorithm for the initial road data reduction (ALGORITHM 1)

In order to solve the sub-problem of optimal bus stops' allocation, the initial road data reduction must be first executed to decrease an enormous number of all possible candidate points obtained by the GIS segmentation (see figure 12 and **ALGORITHM 1**from figure 10). By using this algorithm, the reasonably decreased number of candidate road points can be accomplished.

As it turns out, **ALGORITHM 1** in figure 12 needs the virtual circles of prescribed radius *r*, which must be created for each road point. Then the following two heuristic rules are performed:

1.) If the neighboring road points $p(i), p(i+1)$ are too close to each other, a dilution of them should be conducted in the case that their mutual distance is: $d\left[p(i), p(i+1)\right] < r \cdot r_r$, where r_r is a reduction rate coefficient applied for the practical reasons.

2.) If the observed road point is too far (more than *r*) from any of pupils' addresses points, it must be excluded from the further procedure.

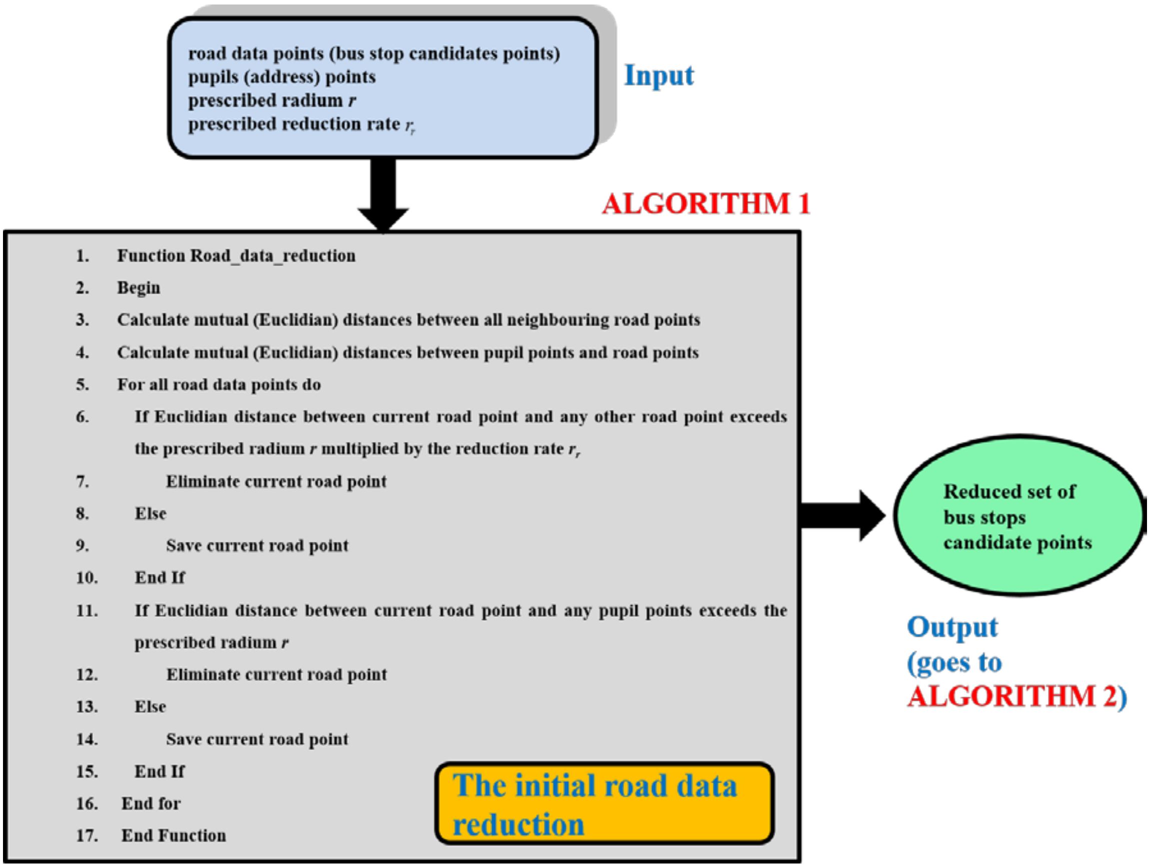


Figure 12: ***ALGORITHM 1*** *for the initial road data reduction*

The algorithm for the optimal allocation of bus stops (ALGORITHM 2)

For optimal bus stops' allocation belonging to the group of *Maximum location covering problems* (MLCP), many methods for solving facility location problems have been developed, e.g.,(Church and ReVelle, 1974; Corrêa et al., 2007; Corrêa et al., 2009; Correia and da Gama, 2015; Desrosiers, 1986). Contrariwise, in this paper, the optimization based on the Monte Carlo simulation method (MCSM) (c.f. figure 13) had been deployed to solve the allocation problem(Dragan et al., 2011; Kramberger et al., 2013). Although our algorithm is likely not so sophisticated as some other random search-based methods for solving the allocation problems (e.g., the Genetic Algorithms or Ant Colony approach(Li and Yeh, 2005; Lingmei et al., 2014)), it still gives quite acceptable allocation results.

In order to effectively use **ALGORITHM 2** in figure 13, the observed municipality's surface must be divided into an adequate number of sub-sectors. Furthermore, it must be examined, which BS candidates provide service to the biggest possible number of pupils for each sub-sector. It must also be taken into consideration, that the minimal walking distance of the pupils to the closest bus stop should not exceed the prescribed radium *r*. This way, the "covered" pupils can be appropriately assigned to the corresponding nearest bus stops. An additional criterion is that the number of "uncovered" (unassigned) pupils (those who exceed the radium r) is as low as possible(Dragan et al., 2011).

The algorithm is designed in the sense that an adequate compromise is found between the highest possible number of covered pupils and the lowest possible number of allocated

BS. In order to avoid the optimal number of BS being rising beyond any reasonable limit, the algorithm is constructed in the manner to provide the service within the radium *r*to the majority of pupils. Contrariwise, the unassigned pupils are addressed individually meaning that they are assigned to the closest calculated bus stop (in these cases the walking distance is bigger than radium *r*).If the distance to the nearest BS for any of these pupils is too big, they might be picked up individually. When the MCSM algorithm is completely finished, the positions of the optimal BS are the final results (for further details see (Dragan et al., 2011)).

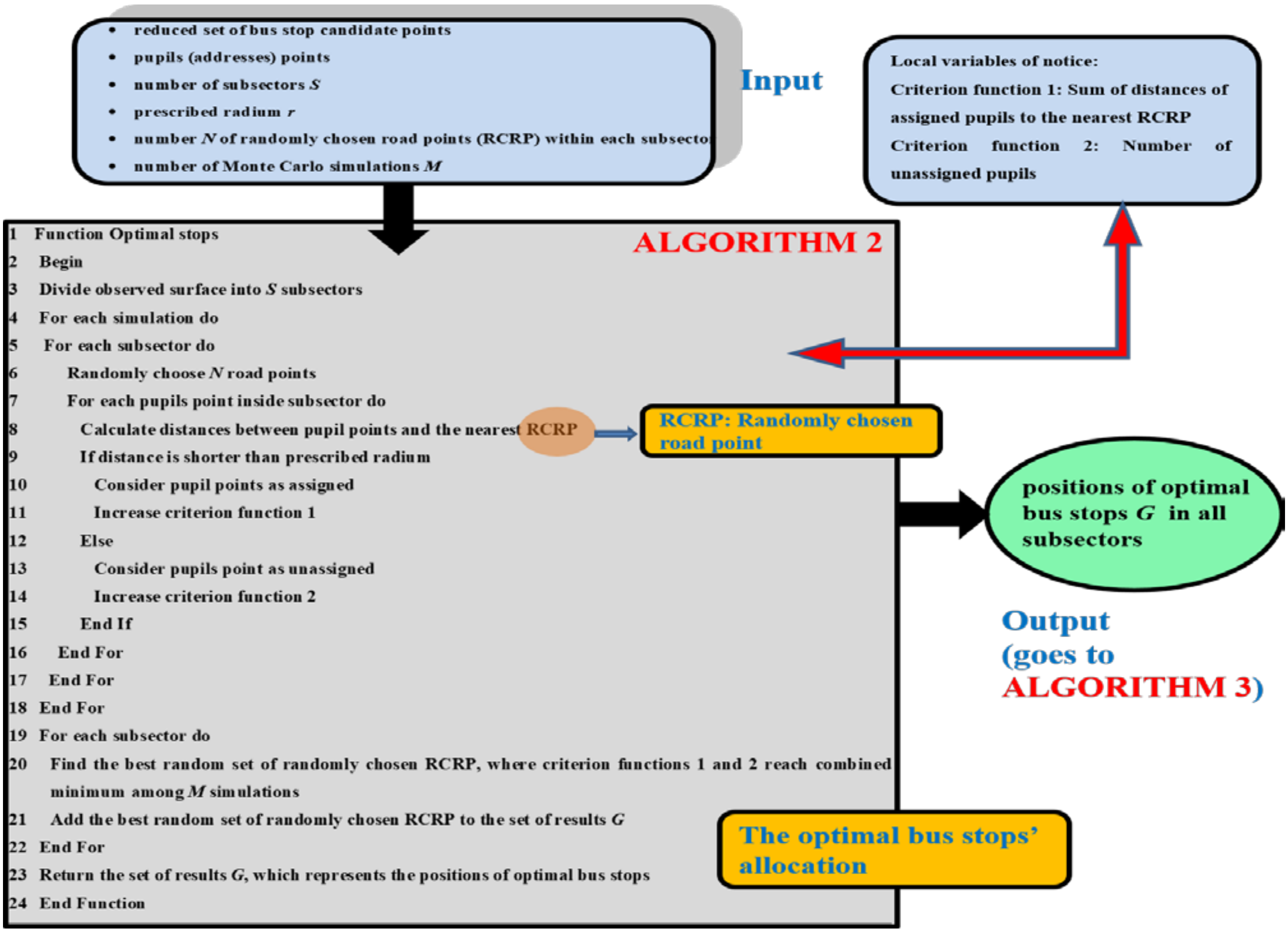


*Figure 13: The MCSM algorithm for the optimal bus stops' allocation (**ALGORITHM 2**)*

The algorithm for the computation of optimal bus routes, driving schedules, driving fleet, VMT, and CO2 (ALGORITHM 3)

For the purpose of optimization of bus routes, driving schedules, and driving fleet, the ESRI Arc GIS software, i.e., its Arc Logistics module has been applied (see figure 14). The latter is a stand-alone end-user application primarily designed for solving the vehicle routing problems (VRP). More information about all algorithms, which are built in Arc Logistics, can be obtained in the literature (Prasertsri and Kilmer, 2003; Weigel and Cao, 1999).

In the MOL, all schools begin with lessons at 8.00, so there is no flexibility about the possible adjustment of schools' starting time. The system of transport operations is organized in such a manner that the drivers of vans start their routes from their home locations. Thus, these additional kilometers must be also considered when **ALGORITHM 3**in figure 14 processes its computations.

In the sequel, it might be appropriate to explain some key characteristics of the Arc Logistics optimization mechanism. The criterion function for the derivation of optimal driving routes can be calculated with respect to the traveling distance in kilometers, or travel time. To do this, the mechanism creates different combinations of scenarios regarding the outcomes of the transportation process according to the different routes, different driving schedules and different loads of the driving fleet (Prasertsri and Kilmer, 2003; Weigel and Cao, 1999).

While executing these scenarios, the travel time in every scenario is calculated based on the known distances and the speed of the vehicles. Namely, in the model of the road network, the length and average (allowed) speed are known for each road section. Consequently, we can calculate the travel time for each road segment, needed for the crossing of this segment. Accordingly, the travel time of vehicles is indirectly considered in the optimization algorithm. When the procedure ends its calculations, the Arc Logistics returns the best scenario as a final result. The latter corresponds to those optimal driving routes, driving schedules, and driving fleet, for which the total traveling distance or travel time is the lowest possible. From observing figure 14 can be noticed, that the **ALGORITHM 3** also calculates the VMT and the CO_2 emissions, related to the final results of the Arc Logistics procedure.

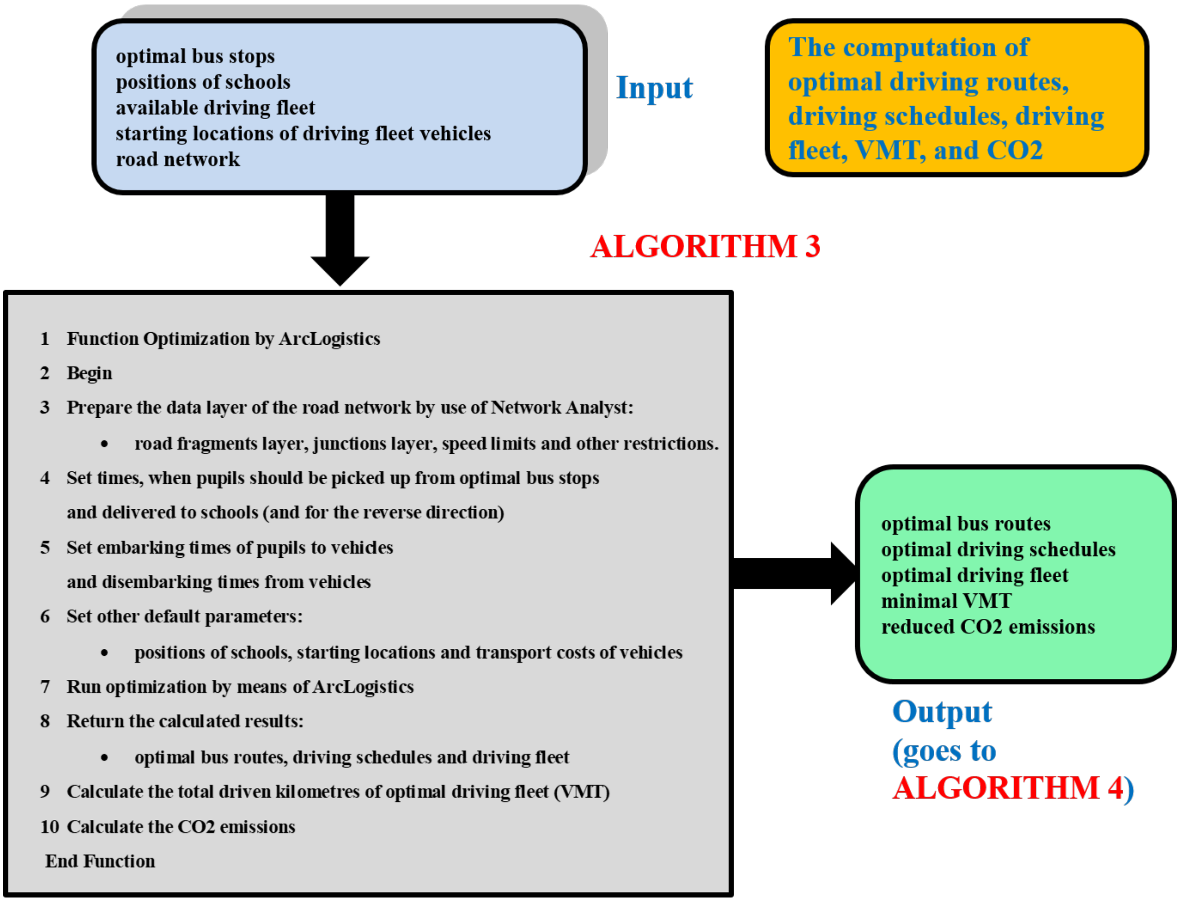


*Figure 14: **ALGORITHM 3** for the computation of optimal driving routes, driving schedules, driving fleet, VMT, and CO_2*

The framework for the calculation and analysis of estimated CO_2 emissions

There exists a variety of approaches for modelingCO_2 emissions that possess different levels of complexity (for details see (Dragan et al., 2016)). These approaches have more or fewer strengths, but also some limitations and weaknesses (Barth et al., 1996; Cappiello, 2002). For the calculation of the CO_2 emissions profiles, as we have already mentioned in the introduction, the two basic approaches are usually adopted (Anable et al., 1997):

- *the Fuel Consumption Method (FCM), and*
- *the VMT approach based on the Emissions Factors' method (EFM).*

The first approach is based on the estimation of emissions from the fuel consumed (represented by fuel sold), while the second approach is based on the distance traveled by the vehicles' type. Thus, contrariwise to the work (Dragan et al., 2016), where quite a complicated approach (MEET model integrated into the MC framework) was used for estimating the CO2 emissions, we have applied in this paper relatively more straightforward FCM and EFM approaches a simpler alternative. Such an alternative might not provide so accurate CO2 estimation as in the case of the MEET model. However, on the other side, due to its relative simplicity, it enables a quick, yet rough, estimation of the CO2 emissions.

5.2.1Thedescription of theVMT approach based on theEmissions Factors' methodfortheestimation of CO2 emissions

This method uses a single emissions rate for each pollutant and vehicle category, which is dependent on the types of vehicle operation. The latter can be expressed in terms of the volume of emissions produced per kilometer traveled. The CO2 emissions can be estimated by the following

simple form(Anable et al., 1997):

$$\begin{aligned} &E_{CO2}(j)(kg\ CO_2) = 10^{-3} \cdot EMF(j)\left({}^{g\ CO_2}\!/\!{}_{km} \right) \cdot d(j)(km), \\ &j = 1, 2, \ldots, n\ (vehicle\ index) \\ &E_{CO2\_TOT}(kg\ CO_2) = \sum_{j=1}^{n} E_{CO2}(j)(kg\ CO_2) \end{aligned} \tag{1}$$

where $E_{CO2}(j)$ are carbon dioxide emissions of the *j-th* vehicle, $EMF(j)$ is the VMT based emission factor of the *j-th* vehicle, $d(j)$ is the total distance of the *j-th* vehicle, traveled in kilometers, and E_{CO2_TOT} are the total CO2 emissions of all vehicles together. In our case, the VMT based emission factors had taken the values based on guidelines(IPCC, 1996, 2006), or they were provided by the vehicles' manufacturers (Kramberger et al., 2013).

Thedescription of thefuelconsumptionapproachfortheestimation of CO2 emissions

The fuel consumption approach calculates the total fuel consumption from each vehicle used by combining the distance figures for each road category with the corresponding official statistics for ${liters}/{100km}$ (Anable et al., 1997). According to the sources (EEA, 2012) and (IPCC, 2006), the CO2 emissions are most adequately calculated on the basis of the type and amount of the fuel combusted, and with respect to its carbon content (IPCC, 2006).

The CO2 emissions calculated by using the fuel consumption approach can be estimated as follows (IPCC, 2006):

$$E_{CO_2}(j)(kg\ CO_2) = EF(j)\left(\frac{g\ CO_2}{kg\ fuel}\right)\cdot FC(j)(kg\ \ fuel),$$
$$j = 1, 2, \ldots, n\,(vehicle\ index)$$
$$E_{CO2\_TOT}(kg\ CO_2) = \sum_{j=1}^{n} E_{CO2}(j)(kg\ CO_2) \tag{2}$$

where $E_{CO2}(j)$ are carbon dioxide emissions of the *j-th* vehicle, $EF(j)$ is the fuel consumption based emission factor of the *j-th* vehicle, $FC(j)$ is the total fuel consumption of the *j-th* vehicle, and E_{CO2_TOT} are the total CO2 emissions of all vehicles together. In our case, the fuel consumption based emission factors had been also taken from the guidelines (IPCC, 1996, 2006).

Since we did not have the access to the information about the FC of the vehicles, i.e., we could not get the insight into the list of fueling invoices, we had to find another way to estimate vehicles' consumptions. We have chosen a simplified approach by applying the multiplication between the vehicle's average consumption per km, obtained from the (EEA, 2012), with the VMT value of the vehicle (in km). This way, the following expression for the FC of the j-th vehicle had been formed:

$$FC(j)(kg\ \ fuel) = AFC(j)\left(\frac{kg\ \ fuel}{km}\right)\cdot VMT(j)(km), \quad j = 1, 2, \ldots, n\,(vehicle\ index) \tag{3}$$

where $AFC(j)$ is the average fuel consumption of the *j-th* vehicle, and the meaning of the $VMT(j)$ is the same as for the distance $d(j)$ in the expression (1). The expression for CO2 emissions then takes the form:

$$E_{CO_2}(j)(kg\ CO_2) = EF(j)\left(\frac{g\ CO_2}{kg\ \ fuel}\right)\cdot AFC(j)\left(\frac{kg\ \ fuel}{km}\right)\cdot VMT(j)(km),$$
$$j = 1, 2, \ldots, n\,(vehicle\ index)$$
$$E_{CO2\_TOT}(kg\ CO_2) = \sum_{j=1}^{n} EF(j)\left(\frac{g\ CO_2}{kg\ \ fuel}\right)\cdot AFC(j)\left(\frac{kg\ \ fuel}{km}\right)\cdot VMT(j)(km) \tag{4}$$

Total fuel consumption for all vehicles can be expressed by:

$$FC_{TOT}(kg) = \sum_{j=1}^{n} FC(j)(kg) = \sum_{j=1}^{n} AFC(j)\left(\frac{kg\ \ fuel}{km}\right)\cdot VMT(j)(km) \tag{5}$$

If the emission factor is approximately equal for all the vehicles ($EF(j) = EF$), we can write:

$$E_{CO2\_TOT}\left(kg\ CO_2\right) = EF\left(\frac{g\ CO_2}{kg\ fuel}\right)\cdot\sum_{j=1}^{n} AFC\left(j\right)\left(\frac{kg\ fuel}{km}\right)\cdot VMT\left(j\right)\left(km\right) = \\ = EF\left(\frac{g\ CO_2}{kg\ fuel}\right)\cdot FC_{TOT}\left(kg\ \ fuel\right) \tag{6}$$

NUMERICAL RESULTS

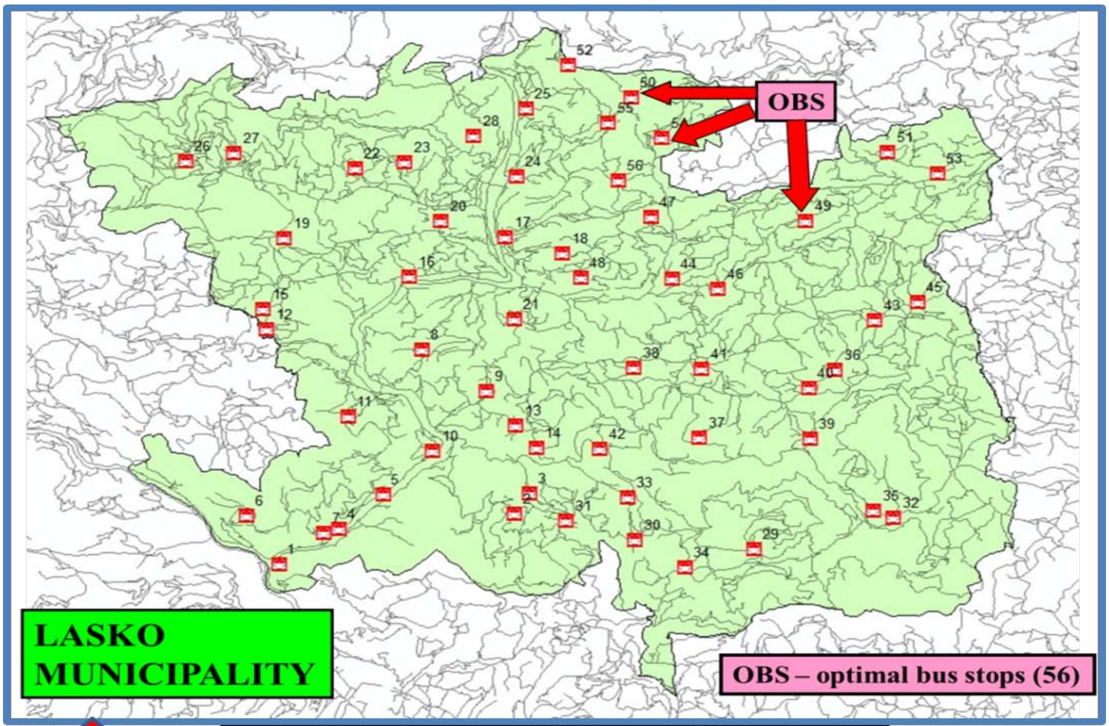
The **ALGORITHM1** for the initial road data reduction and the **ALGORITHM 2** for the allocation of BS were implemented in MATLAB, while the **ALGORITHM 3** was modeled as a VRP problem with Time Windows and was solved by aforementioned Arc Logistics software.

Results for the optimal bus stops' allocation (ALGORITHMS 1 and 2)

Figure 15 shows the results achieved for the optimal bus stops' allocation. The initial number of 14295 BS candidates was reduced to a more acceptable number of 1768 candidates by using **ALGORITHM 1** (the initial road data reduction – see figures 10 and 12). In the next step, 56 optimal BS were extracted from the reduced set of 1768 candidates by using **ALGORITHM 2** (MCSM algorithm for the optimal BS allocation – see figures 10 and 13). Since only 12 pupils of total 562 remained "uncovered" (with a walking distance $d_{WD} > r$), the MCSM has managed to "cover" 97.8% of all pupils (with a walking distance $d_{WD} \le r$).Furthermore, since the walking distances to the nearest BS, of uncovered pupils, are only a few hundred meters bigger than the prescribed radium *r*, their individual treatment should not represent a bigger problem.

The reduction of VMT achieved by means of optimization (ALGORITHM 3)

When **ALGORITHM 3** from figure 14 is completed, the overall optimization procedure from figure 10 is entirely finished. During executing **ALGORITHM 3,** the total distance (i.e. the VMT) of each vehicle per year was calculated for the case of the optimal "simulated" conditions. As it was already confirmed in some of our previous research (e.g., a hypothetical study (Prah, Kramberger, et al., 2018)), the average driving distances are in the case of 3D GIS for circa 4% longer than in the case of 2D GIS. In the next step, the optimal simulated distance has been compared with the real distance for the same year, when the optimization was not conducted yet. For the real unoptimized situation, the information about the distances traveled for each vehicle in one day was given by the municipal administration. On the other hand, the optimized (simulated) distances had been calculated by Arc Logistics. As aforementioned, the real data for the manifestation of comparison purposes were used for the reference school year 2009-2010, which was the last year with out an optimized situation.



Characteristic or the Intermediate result	Value
Number of pupil data points	562
Control area (pupil data points)	247.9 km^2
Control area (road data points)	300 km^2
Number of initial road data points	14295
Number of reduced road data points	1768
Prescribed radium	1.4 km
The reduction rate r_r	0.1
Number of optimal bus stops	**56**
Percentage of covered pupils	**97.8%**
Number of uncovered pupils	**12**

Figure 15: Results for the optimal bus stops' allocation (56 optimal BS)

Table 1illustrates the comparison of the total number of km per vehicle and the entire fleet for the cases without and with optimization, respectively. The comparison for the reference school year indicates that a significant reduction in the total driving distance had been achieved as a result of optimization (*375232 km* without optimization and *292340 km* with optimization). On a yearly basis, this means a decline for *82894kilometers* (*22% decrease* in the total VMT). Moreover, by using the optimization, the VMT for the individual vehicles had been also separately reduced, except for the vehicle 10.

	Without optimization	**With optimization**
Vehicle number	Distance traveled [km/year]	Distance traveled [km/year]
1	47750.5	**34663.5**
2	16044.1	**11759.2**

3	32546.6	**29597.0**
4	45840.7	**30809.1**
5	42020.0	**29101.5**
6	56155.0	**39649.6**
7	36745.2	**33014.2**
8	49660.3	**38655.6**
9	30713.9	**26101.4**
10	17755.7	**18990.6**
Total	**375232**	**292340**

Table 1: The distance traveled in $\left(\frac{km}{year}\right)$ *for the vehicles under the un-optimized (real) situation, and under the optimized (simulated) situation (the reference school year)*

The significant improvement in the case of the optimized situation, when compared to the unoptimized one, can be also illustrated graphically as depicted in figure 16.

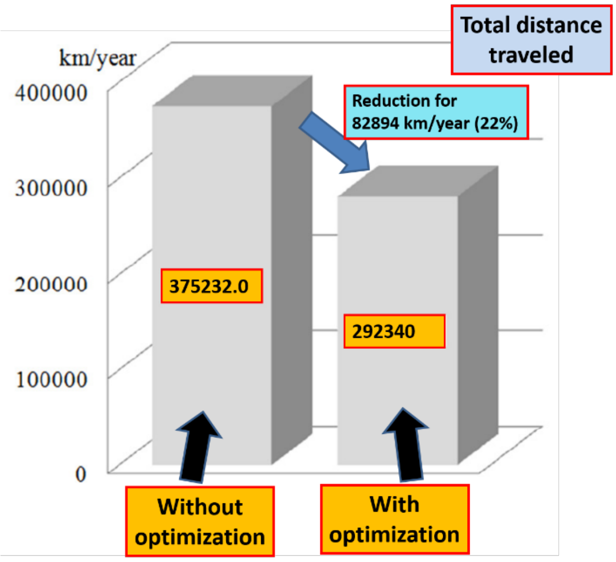


Figure16: The graphical illustration of the total distance traveled in $\left(\frac{km}{year}\right)$ *for the un-optimized (real) situation and for the optimized (simulated) situation (the reference school year)*

6.3The application of the Emissions factor method for the case of real data

For the purpose of the estimation of CO2emissions, the emissions factor method is used at first. Thus, the expression (1) is applied to calculate the estimated emissions, which gives us the results, shown in table 2. These results were calculated on the basis of the VMT presented in table 1, and based on the emission factors, obtained from(IPCC, 1996, 2006), or official web pages of the vehicles' manufacturers.

From table 2 it can be seen that the reduction of total VMT in the optimized case also causes the considerably lower values of CO2 emissions, if they are compared with the values in the unoptimized case. Thus, we have in total only*66861.1*$\left(\frac{kg}{year}\right)$ emissions for the optimized case, instead of *86052.2*$\left(\frac{kg}{year}\right)$ for the unoptimized case. The latter means about 19.2 tonnes/year of CO2 emissions' decrease, which represents a 22.3 % reduction in pollution per one year (see figure 17).

		Without optimization		**With optimization**	
Vehicle number	**Emission factor [g/km]**	**Distance travelled[km/year]**	**CO_2 emission [kg/year]**	**Distance travelled [km/year]**	**CO_2 emission [kg/year]**
1	217	47750.5	**10361.9**	34663.5	**7521.8**
2	221	16044.1	**3545.8**	11759.2	**2598.8**
3	221	32546.6	**7192.8**	29597.0	**6541.0**
4	167	45840.7	**7655.4**	30809.1	**5145.1**
5	280	42020.0	**11765.6**	29101.5	**8148.2**
6	280	56155.0	**15723.4**	39649.6	**11102.0**
7	221	36745.2	**8120.7**	33014.2	**7296.1**
8	221	49660.3	**10974.9**	38655.6	**8542.8**
9	221	30713.9	**6787.8**	26101.4	**5768.4**
10	221	17755.7	**3924.0**	18990.6	**4196.8**
Total	/	375232.0	**86052.2**	292340.0	**66861.1**

Table 2: The results of the emissions factor method: estimated CO2 emissions in $\left({}^{kg}/_{year}\right)$ *for the vehicles under the un-optimized situation, and under the optimized situation (reference school year)*

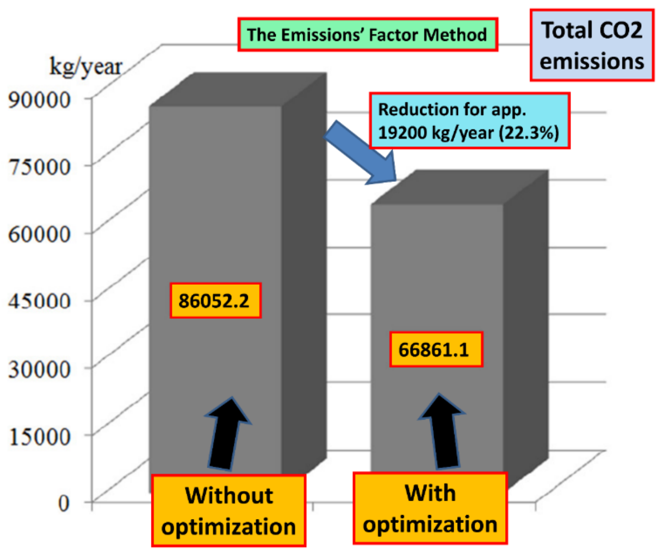


Figure 17: The presentation of the total estimated CO2 emissions in $\left({}^{kg}\!/_{year} \right)$ *under the un-optimized situation, and under the optimized situation (the emissions' factor method, reference school year)*

The application of the Fuel consumption method for the case of real data

The Fuel consumption method is the next method, which has been used for the calculation of theCO2 emissions. In this case, we have applied the expressions (2) and (3) in order to calculate the estimated emissions. The results of these calculations are presented in table 3. The results for the fuel consumption of the individual vehicles (c.f. expression (3)) were estimated on the basis of the VMT values from table 1, and based on the average fuel consumption factors, obtained from the source(EEA, 2012).

Since all the vehicles (vans) can be classified into the class of the »European Diesel Light Duty Vehicles«, the equal AFC factor 0.08 was taken for all of them: $AFC(j)\left(\frac{kg\ fuel}{km}\right) = 0.08, \quad j = 1,2,\ldots,10$. When the values of the fuel consumptions were appropriately estimated by the use of expression (3), they were inserted into the expression (2), where the emission factors, obtained from(IPCC, 1996, 2006), had been also applied. Due to the similarity of vehicles and their relative obsolescence, the equal EF factor 3140 ($EF(j)\left(\frac{g\ CO_2}{kg\ fuel}\right) = 3140,\ j = 1,2,\ldots,10$) was taken for all of the vehicles of the driving fleet.

Vehicle	**Without optimization**		**With optimization**	
	Fuel consumption [kg/year]	**CO2 emissions [kg/year]**	**Fuel consumption[kg/year]**	**CO2 emissions [kg/year]**
1	3820,0	**11994,9**	2772,4	**8707,2**
2	1283,5	**4030,3**	940,6	**2954,1**
3	2603,7	**8175,7**	2367,7	**7435,4**
4	3667,3	**11515,2**	2464,9	**7739,3**
5	3361,6	**10555,4**	2328,5	**7310,0**
6	4492,4	**14106,1**	3171,9	**9960,0**
7	2939,6	**9230,4**	2641,5	**8293,2**
8	3972,8	**12474,7**	3091,5	**9710,3**
9	2457,1	**7715,3**	2087,8	**6557,2**
10	1420,5	**4460,2**	1519,8	**4770,4**
Total	30018,6	**94257,3**	23387,0	**73436,0**

Table 3: The results of the fuel consumption method: estimated CO2 emissions in $\left({}^{kg}\!/_{year} \right)$ *for the vehicles under the un-optimized situation, and under the optimized situation (reference school year)*

The conclusions, which are based on the investigation of table 3, can be treated similarly, as it was for the case of emissions' factor method. Namely, from table 3 it is evident that the estimated fuel consumptions of the vehicles and the corresponding CO2 emissions are significantly lower in the optimized case if compared with the values in the un-optimized case. For instance, we have in total only $73436,0\left(\frac{kg}{year}\right)$ emissions for the optimized case, instead of $94257.3\left(\frac{kg}{year}\right)$ for the unoptimized case. The latter means about 20.8 tonnes/year of CO2 emissions' decrease, which represents a 22.08 % reduction in pollution per one year (see figure 18).

Naturally, there are some differences in the results of both applied methods for the emissions' estimation, since they are based on different methodologies. However, the common thread of both methods is that the estimation of CO2 decrease (in values or %) is quite similar.

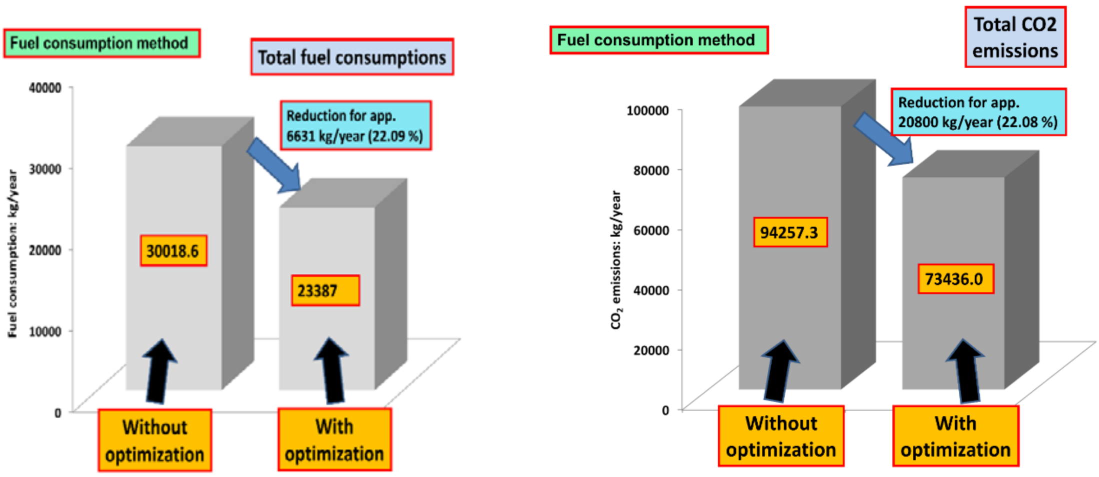


Figure 18: Total estimated fuel consumptions and CO2 emissions in $\left({kg}/{year}\right)$ *for the un-optimized and for the optimized situation (fuel consumption method, reference school)*

Playing scenarios for different AFC factors of the vehicles in the optimized case(fuel consumption method)

If the equal fixed values $AFC = 0.08\left(\frac{kg\ fuel}{km}\right)$ and $EF\left(\frac{g\ CO_2}{kg\ fuel}\right) = 3140\left(\frac{g\ CO_2}{kg\ fuel}\right)$ are taken for all vehicles, the expression (5) takes the form (n = 10):

$$FC_{TOT}(kg) = 0.08\left(\frac{kg\ fuel}{km}\right)\cdot\sum_{j=1}^{10} VMT(j)(km) \qquad (7)$$

while the expression (6) takes the form:

$$E_{CO2\_TOT}\left(kg\ CO_2\right) = 3140\left(\frac{g\ CO_2}{kg\ \ fuel}\right)\cdot FC_{TOT}\left(kg\ \ fuel\right) \tag{8}$$

These expressions for the un-optimized case are (see tables 1 and 3):

$$\begin{aligned} FC_{TOT}\left(kg\right) &= 0.08\left(\frac{kg\ \ fuel}{km}\right)\cdot 375232.0\ km = 30018.56\ kg\ \ fuel \\ E_{CO2\_TOT}\left(kg\ CO_2\right) &= 3140\left(\frac{g\ CO_2}{kg\ \ fuel}\right)\cdot 30018.56\ kg\ \ fuel = 94257.3\ kg\ CO_2 \end{aligned} \tag{9}$$

and for the optimized case are (see tables 1 and 3):

$$\begin{aligned} FC_{TOT}\left(kg\right) &= 0.08\left(\frac{kg\ \ fuel}{km}\right)\cdot 292340\ km = 23387\ kg\ \ fuel \\ E_{CO2\_TOT}\left(kg\ CO_2\right) &= 3140\left(\frac{g\ CO_2}{kg\ \ fuel}\right)\cdot 23387 kg\ \ fuel = 73436\ kg\ CO_2 \end{aligned} \tag{10}$$

Now, let us suppose that the AFC factor is not fixed to the equal value 0.08 for all vehicles (in the optimized case), but it is different for the latter. This means that the vehicles in the optimized case do not have the same average fuel consumption (0.08) in kg per one km anymore, what is, in reality, quite possible. Contrariwise, some of them are supposed to be more greedy. There can be many reasons, why the AFC factor is, in fact, not equal for all vehicles, like: the vehicles have a different age, they are differently maintained, the driving styles are different, the profile of the height kilometers is different, and so on.

Thus, let us now assume that the AFC can take (for the optimized case) three possible values for each vehicle: 0.08, 0.09, and 0.1. Since there are ten available vehicles, this means the total of $3^{10} = 59049$ possible combinations (scenarios). For the latter, the total fuel consumption and corresponding total CO2 emissions of the entire fleet can be calculated. Furthermore, we suppose that the different AFC values for the fleet do not significantly affect the EF factor, and the latter remains equal for all vehicles (3140).

In this context, we are interested, if the optimized values $FC_{TOT}\left(k\right)\left(kg\ \ fuel\right),\ k = 1,2,...,3^{10}$ and $E_{CO2\_TOT}\left(k\right)\left(kg\ CO_2\right),\ k = 1,2,...,3^{10}$, are still lower than the values $30018.56\ kg$ and $94257.3\ kg\ CO_2$, which are belonging to the un-optimized case(with less greedy vehicles all having AFCs equal 0.08) (see (9)), thus irrespective of distributions of the AFCs of the vehicles inside each optimized scenario.

The idea about the different optimized scenarios with respect to the different combinations of AFC distributions of the vehicles is illustrated in table 4. The first (shaded) row corresponds to the best optimized scenario (see (10)) since all the AFCs are equal to the smallest value of 0.08. If we move forward across the scenarios in table 4, the AFC values are gradually increasing for various vehicles simultaneously. By doing this, the worse optimized scenarios are expected ($FC_{TOT}\left(k\right)$ and $E_{CO2\_TOT}\left(k\right)$ are bigger, i.e., the vehicles become greedier) since the joint average fuel consumption of the entire fleet is rising. We also expect that in the case of the last optimized scenario (59049th row), we have reached the worst conditions about the average fuel consumption, since all the vehicles have the biggest AFC value 0.1. Nevertheless, we still hope, that even in this worst optimized scenario with the greediest vehicles, the situation is still better than it was in the un-optimized case (with a less greedy fleet possessing the vehicles all having AFCs equal to 0.08).

Serial number of optimized scenario(*k*)	**AFC for vehicle 1[kg/km]**	**AFC for vehicle 2[kg/km]**	**AFC for vehicle 3[kg/km]**	**…**	**AFC for vehicle 8[kg/km]**	**AFC for vehicle 9[kg/km]**	**AFC for vehicle 10[kg/km]**
1	**0.08**	**0,08**	**0.08**	**…**	**0.08**	**0.08**	**0.08**
2	0,08	0,08	0.08	…	0.08	0.08	0.09
3	0,08	0,08	0.08	…	0.08	0.09	0.08
4	0,08	0,08	0.08	…	0.08	0.09	0.09
…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…
59048	0,1	0,1	0.1	…	0.1	0.1	0.09
59049	0.1	0,1	0.1	…	0.1	0.1	0.1

Table 4: The different optimized scenarios with respect to the different combinations of the AFC distributions of the vehicles

Naturally, when the index k is increasing in table 4, the total fuel consumption $FC_{TOT}(k)(kg)$ is also changing and so is the total value of CO2 emissions $E_{CO2\_TOT}(k)(kg\ CO_2)$. Mathematically, on the basis of expressions (5) and (8), this can be written in the form as shown in expression (11) given below. Here, some additional emulated normally distributedrandom noise $\varepsilon(k) \in N(0,\sigma_\varepsilon^2)$(with a variance σ_ε^2 having some predefined value) that disturbs the AFC variable has also been added in order to move us closer to the reality. By applying the noise, all the variables become the random variables with a stochastic nature, and we can write:

$$\begin{aligned}
&Fuel\ \ Consumption\,(total-all\ vans,\ \ for\ \ k-th\ \ optimized\ \ scenario):\\
&FC_{TOT}(k)(kg\ \ fuel)=\sum_{j=1}^{10} AFC(k,j)\left(\frac{kg\ \ fuel}{km}\right)\cdot VMT(j)(km),\quad k=1,2,...,3^{10}\\
&where\ Average\,Fuel\ \ Consumption\ \ (\,for\ \ van\ j\ and\ scenario\,k)\ \ is:\\
&AFC(k,j)=\{0.08,0.09,0.1\}\left(\frac{kg\ \ fuel}{km}\right)+\varepsilon(k),\quad j=1,2,...,10,\quad k=1,2,...,3^{10}\\
&\varepsilon(k)\in N(0,\sigma_\varepsilon^2) \qquad\qquad (11)\\
&and\\
&CO_2\ \ emissions\,(total-all\ vans,\ \ for\ \ k-th\ \ optimized\ scenario):\\
&E_{CO2_TOT}(k)(kg\ CO_2)=3140\left(\frac{g\ CO_2}{kg\ \ fuel}\right)\cdot FC_{TOT}(k)(kg\ \ fuel),\quad k=1,2,...,3^{10}
\end{aligned}$$

Just explained the principle of playing of optimized scenarios can also be presented graphically, as it is shown in figure 19 (**ALGORITHM 4** from figure 10).

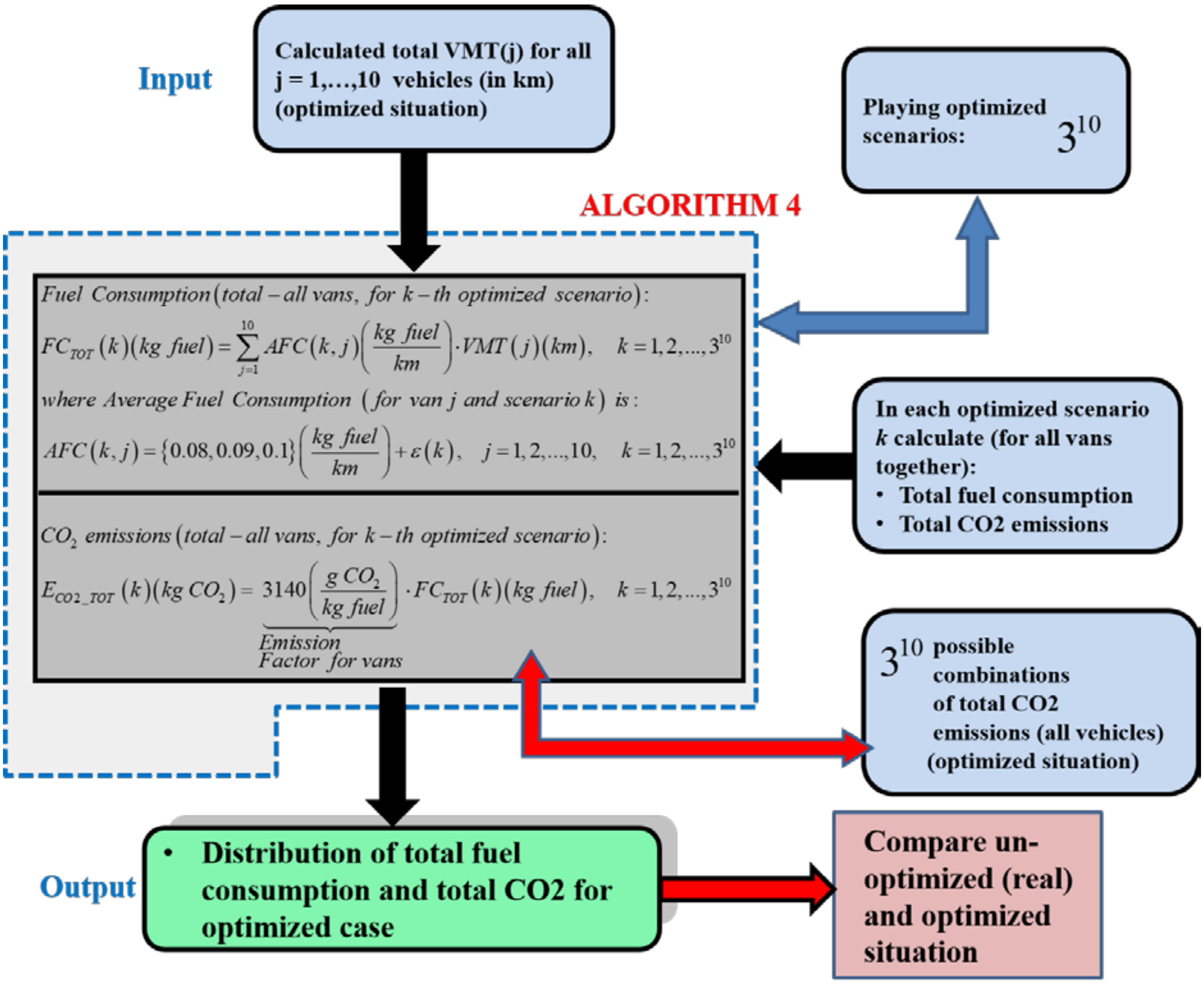


Figure 19: **ALGORITHM 4**for *the playing of optimized scenarios with respect to variations of the AFCs of the vehicles' fleet (AFCs can take three possible values for each vehicle: 0.08, 0.09, and 0.1, resulting in* $3^{10} = 59049$ *possible combinations)*

Figure 20 shows two histograms with respect to all 59049 possible combinations of the optimized scenarios, which are presented in a simplified form with only 30 bins. The first one is related to the calculated total fuel consumptions $FC_{TOT}(k)(kg\ fuel),\ k = 1,2,...,10^3$ of all vehicles, while the second is related to the total CO2 emissions $E_{CO2\_TOT}(k)(kg\ CO_2),\ k = 1,2,...,10^3$ of all vehicles. From figure 20 it is evident, that both distributions have all values below the values of the unoptimized case since both optimized histograms are positioned left from the lines A and B (unoptimized case). It can also be seen, that even in the case of worst optimized scenario (all ACFs equal 0.1), better results were achieved for $FC_{TOT}(kg\ fuel)$ and $E_{CO2\_TOT}(kg\ CO_2)$ (29234 kg of fuel and 91794 kg of CO2) than it was for the un-optimized case with all ACFs equal 0.08 (30019 kg of fuel and 94257 kg of CO2). Thus, in the case of the worst optimized scenario, the decrease in CO2 emissions with respect to the un-optimized case is (94257 – 91794) tonnes = 2.463 tonnes (2.613% drop in pollution).

Bothrandom variables $FC_{TOT}(k)(kg\ fuel),\ k=1,2,...,10^3$ and $E_{CO2\_TOT}(k)(kg\ CO_2),\ k=1,2,...,10^3$ are approximately normally distributed. This is confirmed by two statistical tests, i.e., the Jarque-Berra and Shapiro-Wilks test, whilewealsohaveadequatevaluesforskewnessandkurtosis.Themathematicalexpectations (mean values) are: $E\left[FC_{TOT}(k)(kg\ fuel)\right]=26310\,kg$; $E\left[E_{CO2\_TOT}(k)(kg\ CO_2)\right]=82608\,kg$. Since all values of both optimized histograms are lower than the lines A and B for the un optimized case, there is a strong belief (likelihood) that the emissions for optimized scenarios will always be lower than the ones for the un optimized case.

From just described findings we can conclude that the optimization of VMT was indeed very efficient.Namely, we had managed to significantly reduce the total CO2 emissions even for the cases, when the combinations of average fuel consumptions of the fleet were quite significant and intentionally emulated as bigger than in the caseof normal conditions.

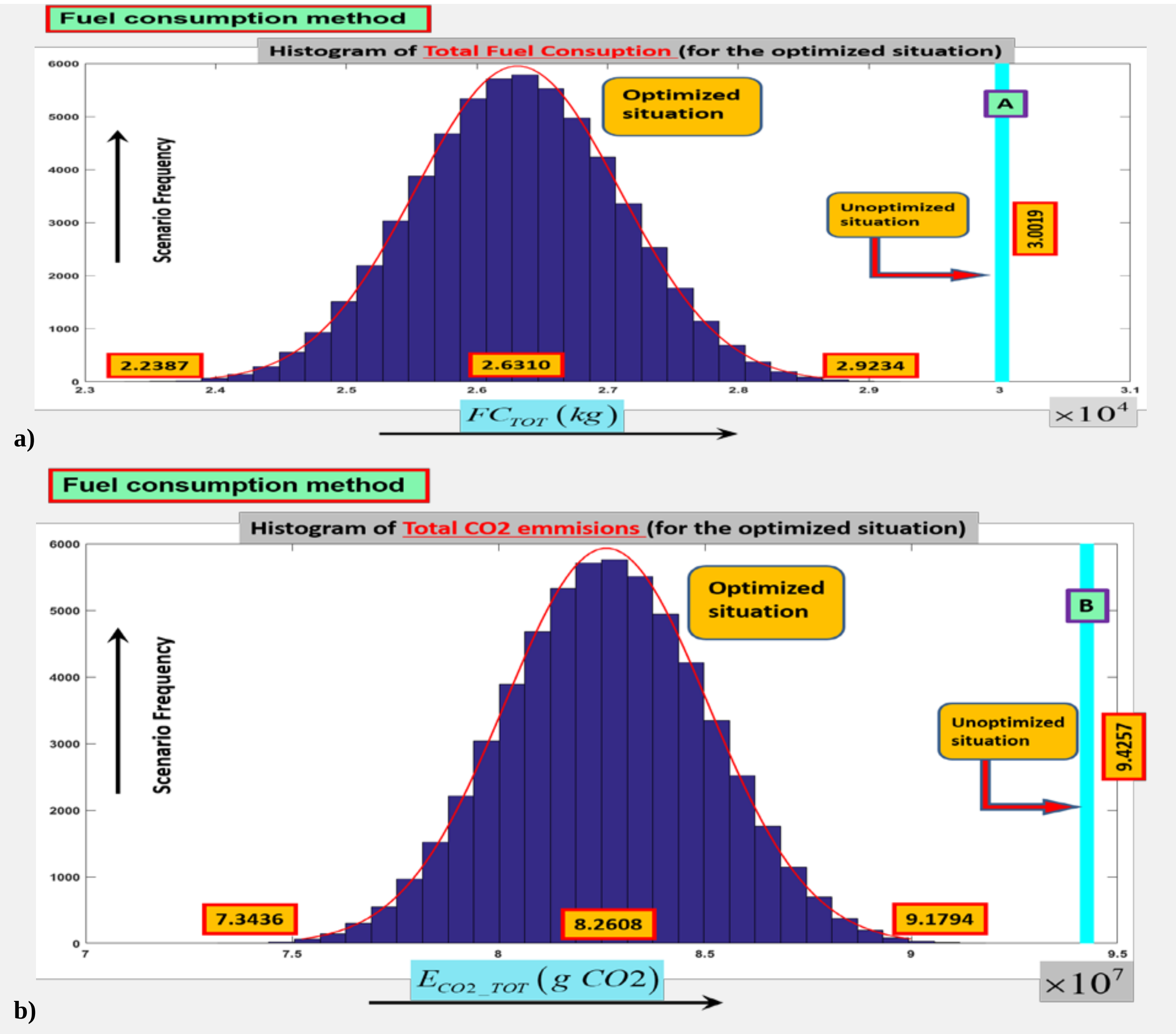


Figure 20: Histograms of all 59049 possible combinations of the optimized scenarios: a) for $FC_{TOT}(k)(kg\ fuel),\ k=1,2,...,10^3$ *; b) for* $E_{CO2\_TOT}(k)(kg\ CO_2),\ k=1,2,...,10^3$

Conclusion

The paper addressed the problem of reduction of GHG emissions, particularly those related to the CO2 in road transport. Among several different approaches, the concept of VMT reduction is chosen in order to decrease CO2 emissions. In order to achieve this goal as much effectively as possible, the heuristic optimization approach combined with the 3D GIS technology has been applied and tested for the case of School Bus Routing Problem in the municipality of Laško.

The conducted approach consists of four stages: the initial road data reduction, the optimal allocation of bus stops, the design of optimal driving routes, driving schedules and driving fleet, and finally, the playing of scenarios for different AFC factors of the vehicles in the optimized case. When these stages are finished, the total VMTs for every individual vehicle and for the entire fleet are calculated for the optimized simulated case. The latter are then compared to the actual un-optimized VMTs, obtained from the municipal administration for the addressed reference school year.

Moreover, for both cases, un-optimized and optimized, the CO2 emissions are estimated based on the given total distances travelled by the vehicles. For the calculation of CO2, two methods are applied, the emissions' factor method, and the fuel consumption method. The innovative algorithm for playing the different scenarios for average fuel consumption of the vehicles of transport fleet is also developed for the optimized case. It is based on the fuel consumption method and is used for changing the distribution of the AFCs of the vehicles. As a consequence of playing of optimized scenarios, the total fuel consumption and related total CO2 emissions of the driving fleet are also changed in each scenario. The results of all optimized scenarios are then compared to the results of the un-optimized case.

The achieved results show the significant reduction of the amount of VMT and consequently the amount of CO2 emissions, irrespective of the method for the calculation of emissions. By application of the used approach, 22% of kilometres every year would be saved if we have applied an optimization approach. Consequently, the significant reduction of CO2 emissions would also be achieved. On the one hand, the emissions' factor method shows the decrease in the quantity of 19.2 tonnes of emissions per year (22.3% decrease), while the fuel consumption method shows the decrease in the quantity of 20,8 tonnes of emissions per year (22.08% decrease).

Just mentioned decrease corresponds to the optimized situation when all the vehicles have the smallest AFC with the value of 0.08. In all other optimized scenarios, when the AFCs of individual vehicles can be bigger than 0.08, the decrease in CO2 emissions is not so obvious. However, despite this, all of these scenarios still lead to significantly lower values of CO2 emissions, if they are compared with emissions in the un-optimized case. Thus, even in the case of the worst optimized scenario, when all the vehicles have AFCs set to the biggest value 0.1 and are the greediest, the decrease is 2.463 tonnes per year (2.613% drop in pollution), if compared with the un-optimized case and less greedy vehicles with AFCs equal to 0.08.

The paper is believed to contribute in the following ways. Firstly, it is shown that the reduction of the VMT using the applied heuristic optimization approach can be an important alternative to specific other, often used approaches to reduce the CO2 emissions in road transport, like alternative technologies or driving behaviour changes. Secondly, it is also shown that even in the case of quite high AFCs of the vehicles, which are reasonably beyond normal conditions, the optimization can still provide the better results than in the case of less greedy vehicles under non-optimal conditions. Furthermore, the developed algorithm for playing the different scenarios for vehicles' average fuel consumption might have represented another unique contribution. Also, the use of the 3D GIS data in the optimization procedure might have been another possible contribution. Since the achieved results are promising, we believe that it would be worthy of continuing with research in the direction of further developing of algorithms presented in this paper. Finally, from a practical point of view, the entire optimization mechanism as a part of a decision support system is successfully running in the observed municipality for several years already, while the cost savings are significant.

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