Research Article

Aleksander Nieoczym, Jacek Caban, Ondrej Stopka*, Tomasz Krajka, and Mária Stopková

The planning process of transport tasks for autonomous vans

<https://doi.org/10.1515/eng-2021-0087>

received July 03, 2021; accepted August 01, 2021

Abstract: Recently, we have seen an increase in interest in autonomous mobility around the world. Autonomous vehicles have enormous potential, and the development of radar, information, communication, and measurement technologies brings us closer and closer to this type of mobility. This article considers the principles of planning and selecting routes for transport tasks. The research on the values of indicators characterizing the transport process was carried out for a simple case, when vehicles move along a fixed route without disturbances. The research used mathematical modelling based on the theory of Markov random systems to determine the capacity of the system, the average length of the queue for service, and the average number of transport tasks. The simulations were carried out for the assumed number of vehicles $m = 15$ and for points requiring service $N = 40$. The ranges were obtained wherein the number of occupied vehicles oscillated around 30% (for $\rho = 0.1$), when all the vehicles were occupied (for $\rho = 0.625$), and when the system became inefficient.

Keywords: autonomous vehicles, transport planning, probabilistic evaluation, vehicle routing problem

* **Corresponding author: Ondrej Stopka**, Department of Transport and Logistics, Faculty of Technology, Institute of Technology and Business in České Budějovice, Okružní 10, České Budějovice, Czech Republic, e-mail: stopka@mail.vstecb.cz

Aleksander Nieoczym: Department of Machine Design and Mechatronics, Faculty of Mechanical Engineering, Lublin University of Technology, Nadbystrzycka 36, 20-618 Lublin, Poland, e-mail: a.nieoczym@pollub.pl

Jacek Caban: Department of Automation, Faculty of Mechanical Engineering, Lublin University of Technology, Nadbystrzycka 36, 20-618 Lublin, Poland, e-mail: j.caban@pollub.pl

Tomasz Krajka: Department of Information Technology and Robotics Production, Faculty of Mechanical Engineering, Lublin University of Technology, Nadbystrzycka 36, 20-618 Lublin, Poland, e-mail: t.krajka@pollub.pl

Mária Stopková: Department of Transport and Logistics, Faculty of Technology, Institute of Technology and Business in České Budějovice, Okružní 10, České Budějovice, Czech Republic, e-mail: stopkova@mail.vstecb.cz

1 Introduction

Autonomous vehicles (AV) are supposed to bring many benefits to society [1]. AV in the long run have significant benefits in terms of transport accessibility, safety, traffic flow, emissions, fuel consumption, and travel comfort. This is confirmed by numerous scientific works [2–11]. Many scientists believe that the implementation of AV will improve the level of road safety [4,9,11]. It will also cause transformational changes in mobility and accessibility [2,5,12–14], as well as energy efficiency and emissions from the transport sector [10,15–17]. Changing the mobility system to autonomous will also affect changes in employment, data availability, management, and business models of various industries related to the supply chain [18–20]. Significant benefits can also be achieved using mathematical optimization methods [21–24].

The localization tasks focus on the problem of determining the position of object in a given frame of reference [25]. Real-time information gathering by the onboard computer is an important element of safe driving when driving an AV. This information is dynamically changing while embracing: the impact of other vehicles in motion, hazards on the route, information on the weather condition, and information on changes in the road infrastructure (e.g., traffic lane turned off, traffic signal failure). It is assumed that the true safety test for AV will be the ability to recreate failure-free and safe driving in a way that can be achieved by a driver in a traditional car.

There are two concepts relating to the design, connectivity configuration, and information gathering of AV. One of them assumes interaction between autonomous and conventional vehicles, while the other assumes the extension of connectivity between the AV and the infrastructure [26]. Both methods of communication and navigation require the development of communication protocols, encrypted security standards, and precise digital recreation of the environment in the form of high-resolution maps.

The currently tested AV use sensors grouped in radar, lidar, GPS, and vision cameras, which, combined with

high-resolution maps, enable onboard systems to identify appropriate navigation paths, as well as obstacles and appropriate markings. Communication is realized in the form of a protocol as follows [26,27]:

- V2X, known as “vehicle for everything,” includes technology that allows vehicles to communicate with the moving parts of the motion system surrounding the vehicle.
- V2V allowing the vehicles to communicate with each other.
- V2I, known as “vehicle to infrastructure,” is the communication that allows vehicles to communicate with external systems such as streetlights, buildings, and even cyclists or pedestrians.

The above technologies require low data transmission latency and involve the use of wireless technologies to achieve real-time two-way communication. V2V and/or V2I (V2X) communication will allow the visibility of other vehicles in a straight line when they are obstructed when the vehicles move in a straight line [28]. It will also enable the acquisition of new information from other vehicles, including traffic, weather, and information about the condition of other vehicles. Information on infrastructure is collected by sensors placed by roads, elements located by lidars, or data available from other vehicles connected to V2V [29]. If the vehicle cannot detect or predict road conditions, the information may be sent from the vehicle in front approaching the danger area [30].

Digital perception should be replicated in AV as algorithmic preprocessing, validation of measured data, and the ability to infer and predict new events through associative and case-based reasoning [31]. In addition to detection, identification, or measurement, an important problem is the correct interpretation and, on its basis, generating a command for automatic steering systems [32].

Transport tasks can be more or less complex and take place in different conditions of the intensity of recalling to the task [33]. This study discusses the principles of planning and selecting routes for servicing transport tasks, and then simulation tests were carried out. The research on the values of indicators characterizing the transport process was performed for a simple case, which assumes that vehicles move along a fixed route without disturbances. The simulation assumed a certain number of vehicles $m = 15$ for points requiring servicing $N = 40$. In the study, it is important to obtain intervals in which we

do not use all the vehicles, when they are occupied, and when the task allocation system becomes inefficient.

2 Mathematical modeling

Sending vehicles to demand points is known as the vehicle routing problem. This problem is combinatorial and belongs to NP-complete problems. Finding the optimal solution becomes more complicated as the number of points reporting service needs increases. The selection of the optimal route must be chosen in a way that follows the decisions of other carriers [34]. When solving this problem, one encounters interdependent optimization issues as follows [26,35]:

- Dividing the set of all delivery/collection points into regions, each of which will be assigned to one vehicle. The location of service points can be defined by GPS coordinates.
- Determining the order of service within the area.
- A situation where none of the vehicles has preliminary information about the target, but has a built-in map with all points within its range marked. Vehicles divide destinations among themselves in order to reach the destination in the shortest possible time. This problem is called the goal assignment problem. Originally, it was used in the operation of unmanned aerial vehicles (UAVs) or in vehicles whose route is determined by a network of sensors.

The problem of mapping the routes for vehicles is the starting point for the formulation of related problems related to the modification of the basic task. This may encompass subjects as follows [35]: determination of vehicle routes with time windows, vehicle routing, delivery and reception, stochastic vehicle routing problem of whether the problem of determining vehicle routes with additions cargo vehicle.

The problem of mapping the routes is solved with the use of heuristic (approximate) methods, which, unlike the exact methods, do not provide certainty of obtaining the optimal solution. The obtained solution is close to the optimal one and acceptable from the point of view of the calculation duration, which is incomparably shorter than in the case of accurate methods. Analyzing system attributes and applying them correctly in a model are important in order to achieve the most accurate results [36].

The heuristic methods proposed so far can be classified into three groups as follows [22,37–39]:

- construction methods,
- decomposition methods,
- methods of growth.

Design methods include algorithms that simultaneously assign recipients to individual vehicles and determine the order of deliveries by a given vehicle. The choice of a vehicle for specific transport tasks can be accomplished in two ways. In the first, the load is assigned to a free vehicle. In a second method, a vehicle that is free at a given moment can be directed to a specific point of delivery/collection that is currently in need of transport service. Another variable introduced is represented by the issue of how the transport task is initiated. There are tasks initiated by delivery/collection points (search for free vehicles) or tasks initiated by vehicles (search for free loads) [40,41].

In decomposition methods, the allocation of recipients to vehicles and the sequence of service by individual vehicles are considered separately. This way of looking for a solution is to shape one route for all recipients served by the supplier, and then divide it into smaller sub-routes served by individual vehicles.

The last group of heuristic methods entails growth algorithms, so called local optimization methods. They are based on the strategy of searching for the optimal solution by replacing the currently considered solution with a new one, representing a better route system. The transformation of the currently considered set of vehicle routes into another one may take place, inter alia, by direct exchange of service points between routes or by transferring service points from one route to another.

In the case of dynamic (online) control systems, simple heuristics are implemented to address the transport task according to the first-come-first-served (FIFO) rule. The first available vehicle is sent to the load that first requested transport service. The transport process can also be carried out according to the first-encountered-first-served (FEFS) rule. This rule is used in distributed dynamic control systems. Transport vehicles capable of carrying many loads at the same time take the first vacant loads encountered, if there is room for them. Then, the transport modules are unloaded at their destination. Simulation studies have shown that for single-loop cases, this type of FEFS heuristics is more effective compared to those using the FIFO rule.

3 Probabilistic evaluation of the operation of simple system

The transport system includes N points requiring servicing by m vehicles [42]. Each point sends reports with the intensity λ , while the intensity of servicing these points by vehicles is μ . The general intensity of reports depends on the task load of a given point, i.e., it is a function of the state of the system. It is assumed that the sequences of time intervals among successive reports sent by points to be serviced are independent of each other and have the same distribution. The service time is a random variable, and with m vehicles, each of them works independently of each other and the service time has the same schedule. In order to determine the capacity of the transport system, the average length of the queue for service, and the average number of notifications, the theory of Mark's random systems is used [43]. It assumes that it is a single-channel system for which the request stream λ is described by the Poisson distribution, while the service time is subject to the exponential distribution. Handling as follows [44]:

E_0 – all vehicles free, no tasks to be serviced,

E_1 – one vehicle busy, one notification in the system,

E_2 – two vehicles seized, two reports in the system.

By introducing successive iterations regarding the number of vehicles and the number of service requests, the following states are obtained [45]:

E_m – m of vehicles occupied, m notification in the system,

E_j – m of vehicles occupied, $j-m$ reports in the queue for service,

E_N – m of vehicles occupied, N points waiting for service, $N-m$ requests waiting for service.

Between the individual states from E_1 to E_2 , the system is routed through the request stream with the intensity $(N-1)\lambda$, because in the E_1 state one service point has already sent the request, so $N-1$ points can already be reported. Between the states E_0 to E_N , the system is guided by the request stream with the intensity $N\lambda$ [46]. Using the mnemonic rule, it is possible to write down the system of differential equations describing the dynamics of the system [42,47]:

$$\begin{cases} p'_0(t) = -N\lambda p_0(t) + \mu p_1(t), \\ p'_1(t) = N\lambda p_0(t) - [(N-1)\lambda + \mu]p_1(t) + 2\mu p_2(t), \\ \vdots \\ p'_i(t) = (N-i+1)\lambda p_{i-1}(t) - [(N-i)\lambda + i\mu]p_i(t) + (i+1)\mu p_{i+1}(t), \quad 2 \leq i \leq m-1, \\ \vdots \\ p'_m(t) = (N-m+1)\lambda p_{m-1}(t) - [(N-m)\lambda + m\mu]p_m(t) + m\mu p_{m+1}(t), \\ \vdots \\ p'_i(t) = (N-i+1)\lambda p_{i-1}(t) - [(N-i)\lambda + m\mu]p_i(t) + m\mu p_{i+1}(t), \quad m+1 \leq i \leq N-1, \\ \vdots \\ p'_N(t) = \lambda p_{N-1}(t) - m\mu p_N(t), \end{cases} \quad (1)$$

or equivalently matrix

$$\overrightarrow{p'(t)} = M \overrightarrow{p(t)}, \quad (2)$$

where: $M = [m_{i,j}, 0 \leq i, j \leq N]$ and

$$m_{i,j} = \begin{cases} (N-i+1)\lambda, & i = j+1, \\ [(N-i)\lambda + \min\{i, m\}\mu], & i = j, \\ \min\{i+1, m\}\mu, & i = j-1, \\ 0, & \text{except.} \end{cases} \quad (3)$$

Since the probabilities should add up to 1, after performing the calculations, we normalize so that:

$$\overrightarrow{p(t+dt)} = \frac{(M+I)\overrightarrow{p(t)}}{\| (M+I)\overrightarrow{p(t)} \|_1}, \quad (4)$$

where:

$$\| \overrightarrow{p(t)} \|_1 = \sum_N^{i=0} p_i(t). \quad (5)$$

and I is the identity matrix with dimensions $(N+1) \times (N+1)$.

We obtain the steady state probabilities by solving the equation:

$$M\overrightarrow{x} = 0, \quad (6)$$

hence:

$$x_i = \begin{cases} \left[\sum_{i=0}^m \binom{N}{i} \rho^i + \sum_{j=m+1}^N \frac{N! \rho^j}{m!(N-j)! m^{j-m}} \right]^{-1}, & \text{dla } i = 0, \\ \binom{N}{i} \rho^i x_0, & \text{dla } 1 \leq i \leq m, \\ \frac{N!}{m! m^{i-m} (N-i)!} \rho^i x_0, & \text{dla } m+1 \leq i \leq N, \end{cases} \quad (7)$$

where:

$$\rho = \frac{\lambda}{\mu}, \quad (8)$$

and $\binom{n}{k} = \frac{n!}{k!(n-k)!}$ is a symbol of Newton.

The probability that r points report the necessity to service is given by the formula:

$$q_{m+r} = \frac{N! \rho^{m+r}}{m!(N-m-r)! m^r \left[\sum_{i=0}^m \frac{N!}{i!(N-i)!} \rho^i + \sum_{r=0}^{N-m} \frac{N! \rho^{m+r}}{m^r m!(N-m-r)!} \right]} \quad (9)$$

However, the average number of applications waiting in the queue:

$$\bar{v} = \frac{N!}{m!} x_0 \sum_{r=0}^{N-m} \frac{r}{m^r (N-m-r)!} \rho^{m+r} \quad (10)$$

Average number of vehicles serving points:

$$\bar{m} = \sum_{i=0}^{m-1} i x_i + m \left(1 - \sum_{i=0}^{m-1} x_i \right) \quad (11)$$

Average number of notifications in the system:

$$\bar{n} = \sum_{i=0}^m i x_i + \sum_{j=m+1}^N j x_j \quad (12)$$

Average time the notifications remain in the system:

$$t_s = \frac{\bar{n}}{\lambda(N-\bar{n})} \quad (13)$$

The average waiting time of notifications in the queue:

$$t_f = t_s - \frac{1}{\mu}. \quad (14)$$

The simulations of sending vehicles to the points service are presented below (Figures 1–4). They were carried out for $N = 40$ points requiring service (i.e., including state 0 in total, we have 41 states) and for the number of $m = 15$ vehicles. We conducted all simulations for the following data sets [48]:

- with the established service intensity $\mu = 0.008$ and three report intensity values $\lambda_1 = 0.001$, $\lambda_2 = 0.005$, and $\lambda_3 = 0.02$ (which corresponds to the values $\rho_1 = 0.125$, $\rho_2 = 0.625$, and $\rho_3 = 2.5$) – Figures 1 and 3,

Figure 1: Simulation of transition between states in $T = 1,000$ consecutive moments of time (starting from state 0 – no pending reports), for $\mu = 0.008$ and values $\lambda_1 = 0.001$, $\lambda_2 = 0.005$, and $\lambda_3 = 0.02$.

- with a set intensity of reports $\lambda = 0.005$ and three different service intensity values $\mu_1 = 0.003$, $\mu_2 = 0.008$, and $\mu_3 = 0.05$ ($\rho_1 = 1.67$, $\rho_2 = 0.625$, and $\rho_3 = 0.1$) – Figures 2 and 4,
- for three different values $\rho_1 = 0.5$, $\rho_2 = 0.8$, and $\rho_3 = 1.2$ – Figure 5.

In Figure 1, on the OX axis, consecutive moments of time are marked, and on the OY axis, the state in which

Figure 2: Simulation of transition between states at $T = 1,000$ consecutive moments of time (starting from state 0 – no pending reports), for a fixed $\lambda = 0$, and three different values $\mu_1 = 0.003$, $\mu_2 = 0.008$, and $\mu_3 = 0.05$.

Figure 3: Simulation of times for the parameters of the exponential distribution $\mu = 0.008$ and $\lambda_1 = 0.001$, $\lambda_2 = 0.005$, and $\lambda_3 = 0.02$ of the presence of reports in the system for 20 randomly generated reports.

the system is at a given moment (i.e., the sum of the number of calls currently handled and waiting for service). The horizontal line at level 15 shows the number of vehicles that support the system. The simulation result presented in the graph shows that with a set call intensity level of $\mu = 0.008$, with a call intensity of $\lambda_1 = 0.001$, the vehicles keep up with the call handling (we have a large

Figure 4: Simulation of times for the parameters of the exponential distribution $\lambda = 0.005$, $\mu_1 = 0.003$, $\mu_2 = 0.008$, and $\mu_3 = 0.05$ of the presence of reports in the system for 20 randomly generated reports.

Figure 5: Probability distribution of individual states in steady state, for $\lambda/\mu = 0.5$, $\lambda/\mu = 0.8$, and $\lambda/\mu = 1.2$.

reserve of free vehicles), and the number of notifications in the system remains low. With the call intensity $\lambda_2 = 0.005$, the system is on the verge of servicing efficiency – the sum of serviced notifications and waiting for service oscillates around the number of available vehicles ($m = 15$). It can be said that in this situation the vehicles are used optimally, with almost no downtime. With the reporting intensity of $\lambda_3 = 0.02$, the system becomes inefficient, the number of notifications in the system increases to the maximum possible level of notifications (40), and 15 vehicles are not able to handle the notifications appearing in the system.

In Figure 2, on the OX axis, consecutive moments of time are marked, and on the OY axis, the state in which the system is at a given moment (i.e., the sum of the number of calls currently handled and waiting for service). As in Figure 1, the horizontal line represents the number of vehicles servicing the system ($m = 15$). The simulation result presented in the graph shows that with a set reporting intensity level of $\lambda = 0.005$, with a request processing intensity of $\mu_3 = 0.05$, the vehicles keep up with the service of requests, and the number of requests in the system remains low. With the call handling intensity of $\mu_2 = 0.008$, the system is on the verge of service efficiency – the sum of handled notifications and waiting for service oscillates around the number of available vehicles ($m = 15$). With the intensity of handling reports at the level of $\mu_1 = 0.003$, the system becomes inefficient, the number of reports in the system grows significantly above the number of vehicles handling reports.

Figures 3 and 4 show a simulation of the time the declarations remain in the system for 20 randomly generated reports for various parameters of the exponential distribution.

The numbers of consecutively generated reports are marked on the OX axis, and their residence times in the system on the OY axis. The times of residence of the requests in the system presented in the graph are the times generated from the exponential distribution with the parameter $\left(\frac{\lambda(N-\bar{n})}{\bar{n}}\right)$. They correspond to the times when a randomly selected 20 notifications will be present in the system in its steady state. The presented diagram shows that with the set call intensity level $\mu = 0.008$, for the call intensity level $\lambda_1 = 0.001$ (orange points), the reports stay in the system for a relatively short time and their handling is efficient. For the reporting intensity $\lambda_2 = 0.005$ (green points), the service time is correspondingly greater, while with the reporting intensity $\lambda_3 = 0.02$ (blue points) corresponding (as shown in Figure 3) to an inefficient handling system, they are very long (in some cases exceeding even simulation time).

The numbers of the generated times are marked on the OX axis (they have nothing to do with the time t), and on the OY axis their duration in the system. The times of residence of the requests in the system presented in the graph are the times generated from the exponential distribution with the parameter $\left(\frac{\lambda(N-\bar{n})}{\bar{n}}\right)$. They correspond to the times when a randomly selected 20 notifications will be present in the system in its steady state. The presented diagram shows that with a set call intensity level of $\lambda = 0.005$, for a call handling intensity of $\mu_3 = 0.05$ (blue points), the reports stay in the system for a relatively short time, and their handling is efficient. For the report handling intensity $\mu_2 = 0.008$ (green points), the handling time is correspondingly greater, and for the report handling intensity $\mu_1 = 0.003$ (orange points) corresponding (as shown in Figure 4) to an inefficient handling system, they are very long (in most cases even exceeding the simulation time).

In Figure 5, the stationary probabilities of individual states are presented. Individual states (from 0 to 40) are marked on the OX axis, and on the OY axis, the probability of staying in these states in a steady state for different values of ρ .

The OX axis shows the individual states (the number of requests in the system), and the OY axis shows the probability that the system in a steady state will be in the state marked on the OX axis.

From the presented probability distributions, it can be concluded that the value of the coefficient $\rho = \frac{\lambda}{\mu}$ plays a key role in the context of the probability of individual

states in which the system is in a steady state. As for the small values of ρ (as in the situation depicted in red $\rho = 0.5$) corresponding to the situation in which the service of reports is faster than the rate of new reports in the system, the maximum probabilities refer to the states wherein not many reports occur in the system notifications (for the situation presented in the chart (Figure 5), the maximum probabilities correspond to 10–15 notifications in the system). For average values of ρ (as in the situation presented in the graph with green color $\rho = 0.8$) corresponding to the situation in which the service of notifications takes place at a similar pace as the rate of new notifications in the system, the maximum probabilities refer to the states in which the system is in the average number of notifications (for the one presented in the chart (Figure 5), the maximum probabilities correspond to 19–25 notifications in the system). For large values of ρ (as in the situation $\rho = 1.2$ shown in the graph in blue) corresponding to the situation in which the service of reports is slower than the rate of new reports in the system, the maximum probabilities refer to the states in which the system is in a large number of notifications (for the one presented in the chart (see Figure 5), the maximum probabilities correspond to 27–31 notifications in the system).

4 Conclusion

The article considers the principles of planning and selecting routes for servicing transport tasks. The simulations were carried out for the assumed number of vehicles $m = 15$ and for points requiring servicing of $N = 40$. Based on the simulation tests performed, the ensuing conclusions can be summarized as follows:

- The described system is in a state of equilibrium when the number of calls coincides with the service time, that is, when $\rho = m/N$ or $\rho = 0.375$ in our example. For $\rho = 0.1$, the number of seized vehicles oscillated around 30%; for $\rho = 0.625$, in the vast majority of the time, all the vehicles were already occupied; and for $\rho = 1.6$, the system became inefficient (see Figures 1 and 2). Given the N points with an estimated value of ρ , the number of vehicles serving this system should be $m_0 = \rho N$ with a possible variation of about 30%.
- Assuming the significance level $1 - \alpha = 0.95$, then with a probability lower than α , at least one order may appear at a time, processed for a period longer than $-\frac{\tilde{n}}{\lambda(N - \tilde{n})} \ln(1 - \sqrt[3]{1 - \alpha})$. From Figures 3 and 4, we can see that even in the best situations of $\rho = 0.125$ and

$\rho = 0.1$, there are orders the handling of which takes as much as 30% of the entire simulation time. It seems that such orders are quite likely. The transport system is very heterogeneous; there are orders handled very quickly and there are those whose handling is very long.

- The heterogeneity of the system can also be seen in Figure 5; almost all the states (except a few initial states) have quite a high probability of occurrence in the range ρ under consideration. Although the stationary distribution of the probabilities is unimodal, it is nevertheless with a large degree of scatter.

Acknowledgments: This manuscript was supported as part of the research project entitled “Autonomous mobility in the context of regional development LTC19009” of the INTER-EXCELLENCE program, the VES 19 INTER-COST subprogram.

Conflict of interest: Authors state no conflict of interest.

Data availability statement: The authors declare that the manuscript is an original work of the author. It has not been published in other periodicals and is not being in the review process of other journals. The authors confirm the data availability for the purpose of the journal Open Engineering.

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