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# COMPUTATIONAL INTELLIGENCE AND MACHINE LEARNING IN TRAFFIC AND TRANSPORTATION

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***Abstract***

*Nowadays smart phones, embedded systems, wireless sensors and various other devices are widely used, networked and part of the Internet of things. Such devices daily generate big datasets which are unstructured and potentially very useful as aid for solving complex problems. This paper presents general ideas how computational intelligence and machine learning are used to analyze such data and to optimize traffic and transportation. Essence of the application of computational intelligence and machine learning is to use typical patterns of behaviour and data correlations to envision future events and thus provide aid in making correct decisions regarding them. Anticipation of behavior of traffic participants, choice of adequate routes and proper vehicle directing provide that transportation costs are lowered and that human resources are better utilized, that environmental protection is well considered and finally that overall quality of life is enhanced.*

***Key words**: computational intelligence, machine learning, traffic, transportation network*

## 1 INTRODUCTION

The impact of traffic and transport on the modern economy and society has been growing over the last few decades. Connecting transport - distribution centers and production centers, as well as increased mobility of individuals lead to an increase in demand for efficient transport solutions. For successful transportation, the most important thing is the formation of optimal traffic and transport networks in combination with the direction of vehicles and goods.

With the advancement of technology in communication and navigation, the ability to make real-time decisions is becoming very important in transportation. Big data has a significant impact on the development of functional smart cities and support for modern society. The continuous development of micro and macroeconomic entities is based on the principle of interconnection, digitalization and automation, because computational intelligence is considered one of the main activator for transport optimization.

## 2 COMPUTATIONAL INTELLIGENCE AND MACHINE LEARNING

Computational intelligence (CI) is the theory, design, application and development of biologically and linguistically motivated computational paradigms, where a computer learns a specific task from data, experimental observation, expert knowledge or else. CI mainly deals with the "nature-inspired" paradigm, which involves the study of adaptive mechanisms to enable or facilitate intelligent behavior in complex and changing environments. These mechanisms include those paradigms of CI that demonstrate the ability to learn or adapt to a new situation, to generalize, discover and connect [1].
The application of CI describes a set of methods and tools that often imitate biological or physical principles for solving problems that are difficult to solve by mathematical and traditional modeling due to high complexity, uncertainty and stochastic nature of the process [2].
CI mainly uses techniques that exceed a certain symbolic level, i.e. the problem is represented by numbers, which allows more efficient approximations in a reasonable computation time. They often use nondeterministic, stochastic components, heuristics and metaheuristics, which quickly approach one or more solutions in conditions of uncertainty, moving goals and changes in the search space. Also, they are error tolerant and generally suitable for parallelization. However, the biggest drawback is that often there can be no theoretical guarantee that an optimal solution will be found [3].
Three aspects that can characterize artificial intelligence:

- these methods are inspired by nature,
- they solve complex problems without much knowledge that is specific to the problem and
- they are suitable for solving problems in the real world [3].

The most commonly used methods of CI are fuzzy logic (FL), neural network (NN), swarm intelligence (SI), evolutionary computation (EC) and artificial immune system (AIS). FL represents logic similar to human reasoning, where on the basis of approximate values and incomplete or ambiguous data, approximate solutions or conclusions are given. NNs are inspired by actual biological neural networks of the brain of animals or humans, where data are processed through a network of interconnected artificial neurons that identify the relationships between input and output data and find patterns. SI represents the collective behavior of self-organizing systems with multi-agent, which mainly helps to solve optimization and search problems (distance minimization). EC applies biological mechanisms of evolution using the principle of survival of the most capable, and is most useful in solving the problem of optimization and search problem for nonuniform search spaces. AIS is inspired by the immune system of humans, animals and plants, adapting the characteristics and processes of the immune system for learning and memorizing and has the greatest application in adaptive problem solving systems [3]. These models are applicable to many areas, from storage to forecasting and decision making, and may prove more efficient due to their non-parametric nature. Contrary to popular belief, some CI tools may have significant similarities to classical statistical models [4].

Popular and successful CI methods for optimization and planning problems are heuristic optimization approaches such as evolutionary algorithms (EA), local search, and other types of guided search methods. These methods do not take into account all possible solutions, but move "heuristically" through the search space in search of top solutions. Heuristic optimization approaches must be balanced, as they focus on the search for high quality solutions and diversification, which ensures that the search can escape local optimums and does not focus on small parts of the search space. We can say that heuristics is a logic-based algorithm, designed to work fast and provide very good solutions, although not always the best one. Metaheuristics is a higher level strategy that guides other heuristics in search of improved solutions.

Given the availability of big data, data analytics is needed to convert data into meaningful information, which plays an important role in traffic and transportation. Machine learning (ML) approaches offer tools for modeling patterns and correlating data to discover relationships and anticipate potential solutions based on unprecedented events. ML is the study of computer algorithms that can improve automatically through experience and by the use of data, i.e. it can be said that ML deals with learning from data. The ML approach consists of supervised learning (learning from tagged data), unsupervised learning (discovering hidden patterns in data or extracting traits) and reinforcement learning (goal-oriented learning in dynamic situations) [2].

ML deals with the question how to make computers that improve automatically through experience. It is one of the fastest growing technical fields of today, which lies at the intersection of computer science and statistics. This is basically CI and data science. Recent advances in ML have been driven by the development of new algorithms, learning theory, the expansion of online data availability, and low-cost computing. The use of large amounts of data allows ML methods to be found in science, technology and commerce, allowing more evidence-based decisions to be made.

## 3 MODERN TRAFFIC FLOWS AND TRANSPORT NETWORKS

Urbanization, smart cities and technology development can be seen as three pillars that transform transport. Today, urban areas are considered the dominant type of settlement, which is why the optimization of traffic and transport has a significant role in sustainable urban development [5]. The transport system should be interconnected and intelligent. In this context, there is a growing interest in finding new technologies that will support the transport system. Some of the most prominent are mobile communications, cloud technologies, energy storage, autonomous vehicles and the Internet of Things (IoT). IoT consists of various devices or objects, such as sensors, actuators, mobile phones, etc. that are able to communicate with each other and cooperate with neighbors through unique addressing schemes in order to reach common goals [6]. By continuously collecting, analyzing and redistributing information, IoT networks can provide valuable real-time information to passengers and operators and thus support and improve intelligent transport system (ITS), transport systems, etc.

As far as traffic is concerned, mobile phone counting is systematically used to extract traffic information in the form of volume, speed and density in the urban and suburban traffic network [7]. Data based analyses, whether large or not, have been recognized as a valuable tool for transportation operations. The use of big data is a task by which data is transformed into knowledge [8].

Each step towards the ultimate goal involves a series of tasks, which is shown in Figure 1. In the analysis phase, the focus is on discovering anomalies, patterns, and relationship complexes. The prediction step involves complex and flexible data-based models that can consistently and accurately provide information about future conditions, while the final step is mechanisms for creating and disseminating information. Obviously, with the advent of multi-source data collection systems, traffic and transport data sets will not become perfect. Working with large data brings a focus on size, the ability to model unstructured data, and multidimensionality in data sets, as well as the importance of correlation along with causality. The need to develop new paradigms of analysis is addressed by new forms of statistical thinking and models of artificial intelligence [8].


***Fig. 1*** *Process in data analysis*

CI is a new phenomenon in transport modeling, because it can be used to develop scalable, manageable, adaptable and accessible transport systems that use classical reasoning, perception and learning, as well as autonomy [8]. The ability to increase or replace human skills speeds up processing and increases productivity, leading to improved accuracy and quality of results.

Throughout the data learning process, several phases of modeling can occur that can be formulated as optimization problems. In non-stationary environments and transport problems, dynamics can impose different optimal solutions in relation to time and space. This means that optimization should be able to solve dynamic problems and is constantly approaching a solution. CI approaches have structural flexibility and the ability to learn, dealing with complex multiple problems that vary over time [9]. It has been established that CI behaves well in non-stationary and distinctly nonlinear problems [10].

Genetic algorithms can be considered the first and leading technique of CI in transport optimization problems that are systematically applied to network design problems [11], vehicle routing and distribution problems [12]. However, agent based modeling has attracted significant attention in the transport system. Agent and multi-agent systems have been applied to many traffic and transportation subsystems, including dynamic congestion routing and management [8].
In the near future, all movements (humans and machines) are expected to have a unique identity and operate in a smart social and environmental environment, requiring advanced data analysis and optimization skills to solve complex problems and materialize advanced transportation ideas.
A critical issue that will dictate the future of CI in traffic and transport is the possibility to make full use of it, i.e. to become a key technology for improving the efficiency, safety and environmental compatibility of traffic and transport systems [13]. Until now, CI applications have been limited to certain modules of ITS applications, especially for data analysis and forecasting, neglecting their powerful data management and decision-making capabilities [14]. Extended use of CI techniques is needed to take full advantage of their unique capabilities.

## 4 TRAFFIC FLOWS PREDICTION AND TRANSPORT OPTIMIZATION USING COMPUTATIONAL INTELLIGENCE AND MACHINE LEARNING

Traffic flows are one of the most important influences for the formation of a good model of transport due to the optimization of routes, anomalies on the road, the occurrence of traffic accidents.
Transport plays an important role in many companies. Process optimization directly affects the efficiency of the company, which leads to better revenues. Using global communication, new instructions for moving goods can be issued at any time, allowing for faster customer service. Harnessing these new capabilities in the best possible way is therefore an important issue. Traditionally, transport problems are optimized using a static model, i.e. plans are made in advance and then executed. The main problem is that the plans are not made for real-time adjustment, which results in plans that are not too flexible and therefore cannot be easily adapted to the changes that may be needed. Due to the above, there is a need for the optimization problems under consideration to be dynamic, which means that they must be solved online, as time passes. This type of problem is often difficult to make when making a decision at one point, and especially when there is not much time between the next two moments. In order to be able to do this, the optimization algorithm must have an appropriate degree of adaptability.
In dynamic optimization, the goal is to optimize a function F over a period of time. Variables in optimization in this time range represent the decisions that need to be made. F may depend on the previous decision, because if only the current situation is taken into account, then the decision immediately becomes optimal. Future changes in F, as a result of the decisions made now, must be taken into account, which means that F must be optimized not only for the current situation, but also for future situations [15].
Optimizing future, simulated situations is not the only approach to performing expectations. The anticipation can also be done with a heuristic approach, where not only the quality of the current plan is measured, but additional information such as flexibility, complexity and sensitivity are also taken into account.
Because the expectation method for different examples requires the optimization of a combination of decisions and scenarios, methods have been developed that approximate the expectation method [16]. They are usually faster, but result in lower quality solutions. However, there is a problem with most methods if the decision is related to continuous variables, which is why there is a need for CI algorithms that are able to come up with good solutions at any time and are not limited to solving discrete optimization problems with only a few alternatives decisions that can be chosen at any time. Good choices for this are: EA [17], because they use a set of solutions, not just one solution; and statistical / machine learning (ML/SL) used to predict future values taking into account the problem of specific variables and / or quality of decisions. However, the combination of EA with ML/SL optimizes decisions not only in terms of the current situation, but also future decisions with regard to predicting the future situation. Typical examples in traffic and transport are vehicle routing [18] and traffic flow prediction [19]. By carefully analyzing what should be predicted, learning from past experience and explicitly incorporating it into predicting the consequences of current decisions, better results can be achieved than when no prediction is used or when implicit predictive tools are used.

### 4.1. Application of computational intelligence in predicting traffic flows

Traffic forecasting is attracting increasing attention in the field of CI research due to the increasing availability of large amounts of traffic data and their importance in the real world. The key challenge in traffic prediction lies in the way of modeling complex spatial dependencies and time dynamics. Although both factors are taken into account when designing the model, most published papers set strong assumptions about spatial dependence and time dynamics, where spatial dependence is stationary in time, while time dynamics is periodic.
Typical forecasting models include neural network models [20], autoregressive models of integrated moving media (ARIMA) [21], Bayesian network approach [22] and Markov networks [23], as well as the SARIMA model in combination with three known adaptive filter models: Kalmanov filter, least squares recursive filter and least squares filter. The results show that the predictions obtained from the recursive adaptive filtering method are quite good. Adaptive plug-and-play filters are proposed as self-adjusting predictors, which are ideal for application in real-time control and monitoring systems. The dynamic filter provided an adaptive seasonal model of time series to predict short-term traffic flow. A crucial step in the application of this approach is the presentation of the basic parameter of the model in the appropriate space [24]. Support vector regression (SVR) models have been shown

to represent an interesting trade-off between prediction accuracy and computational efficiency, as they are specifically designed to benefit from typical seasonal traffic movements. SARIMA in combination with the Kalman filter represents an approach that is particularly competitive when considering predictions during very congested periods. Unlike classical statistical approaches, relational learning algorithms can easily deal with multiple sources of information [25].

While these methods have studied traffic time series for each individual location, studies in recent years have begun to take spatial information into account. The problem of real-time traffic prediction using real-world sensor data for road networks has been solved by the hidden space network model (LSM-RN) where challenges are solved completely, due to complex topological dependencies and great dynamics associated with changing road conditions. Through a series of road network images, the boundaries of attributes that span both topological and temporal properties are covertly learned. Hidden modeling of road network space with time-dependent weights accurately estimates traffic patterns and their development over time, where an additional network algorithm is set in the model that learns sequentially and adaptively, changing the hidden attributes from the time schedule. This framework allows real-time traffic prediction using real-time sensor readings to adjust / update existing hidden spaces and train models on how data is collected and make predictions on the fly [26].

Further research considers the usefulness of external text data, such as place types, weather conditions and event information, where instead of predicting future traffic based on historical flow data, the goal is to model the correlation between traffic and external urban data sets, such as are points of interest, geographical dimensions, weather conditions and vehicle collisions and the study of their impact on traffic [27].

The problem of traffic prediction is an inspiration for new studies because approaches based on traditional time series models cannot explain the nonlinear space-time dependence, which is why CI (ML, depth learning) comes to the fore.

However, these methods of traffic prediction have limitations: spatial dependence between locations relies only on the similarity of traffic observed through historical data, where models learn static spatial dependence, while another limitation is ignoring shifts in long-term periodic dependence. Traffic data show strong daily and weekly periodicity and dependencies based on such periodicity can be useful for prediction, but the problem is that traffic data are not strictly periodic, as is the dependence between locations that can change over time. In the study [28], the spatial dependencies between locations are presented dynamically and the temporary dependence follows a daily and weekly pattern but is not strictly periodic due to its dynamic temporal shift. In a space-time dynamic network (STDN), a flow mechanism has been introduced to learn the dynamic similarity between locations and a periodically shifting attention mechanism is designed to handle long-term periodic time shifts simultaneously. This method is shown in the data from taxis and bicycles obtained in New York, where a comparison was made with different models for traffic forecasting [28].

### 4.2. Solving the problems of a Travelling Salesman by applying computational intelligence and machine learning

The development of information and communication technologies has enabled dynamic, heterogeneous and uncertain collection of data of large volume and complexity that are used for analysis and interpretation. Geographic information system (GIS) is used to better model real situations and simulate real processes. Its features are integrated into data specifications and computer applications

[29]. Many ITSs work with such modern data components. One example of transport problems is the problem of the commercial traveler (TSP), which has many variants, designed either for the application of mathematical methods of solving or for better modeling of real situations [30]. ITS aims to provide efficient services related to different types of transport, making transport networks smarter. They are based on a variety of technologies, which can range from basic car navigation systems or traffic signal control systems to advanced applications that integrate live data from other sources, such as parking guidance systems [31]. Predictive techniques are designed to allow advanced modeling and comparison with historical data [32]. The advantage of artificial intelligence data analysis applications over other alternatives lies in their flexibility, their ability to detect unknown mechanisms and covariance unattainable for statistical approaches, their accuracy and their ability to cope with dynamically large changes in data. ITS can use methods based on artificial intelligence to solve TSP [33].

*Definition of TSP*. On a complete graph $G = (V, E)$, where is *V* set of *n* topics, let it be $D = \left(d_{ij}\right)_{1<i,j<n}$ distace matrix related by E. The goal of the TSP is to find the minimum distance in a Hamilton route (i.e., the minimum length of a route that passes through any topic once and only once) [34].

From the point of view of computational complexity, TSP is a difficult problem, which means that in a short time it is unlikely that an exact algorithm will be found for the most complex case [35]. The large TSP is difficult to solve from a computational point of view, which is why researchers have focused on approximate and heuristic approaches [36]. The best approximate solutions for symmetric TSP are provided by Concorde [37]. Heuristic methods have good empirical behavior. One of the most well-known heuristic algorithms of local searches is Lin-Kernighan (LK), which starts from a given tour and improves it by switching to 2, 3 or more edges [38]. Other successful approaches are metaheuristic applications. For example, to perform many efficient algorithms for TSP has been used ant colony optimization (ACO) [39]. ACO is a metaheuristic framework for solving optimization problems, inspired by the way in which ant colonies find the shortest path. In a study [34], algorithms have strong links to Q-learning [40]. The ant system (AS) [41] is a special case, i.e. the first ACO implementation belonging to the Ant-Q family [42]. Assume that the TSP has n nodes, completely connected by edges of length that form a symmetrical square, a positive matrix $D = \left(d_{ij}\right)_{1\leq i,j\leq n}$. Initially, a colony of $m$ artificial ants was randomly distributed in nodes. Each edge receives

an initial pheromone value $\tau_0$. During execution, the pheromone values at the edges form a symmetrical square, a positive matrix $\left(\tau_{ij}\right)_{1\le i,j\le n}$. A heuristic function is defined that guides the construction of the solution at the edges as inverse distances:
$\eta_{ij} = 1/\left(d_{ij}\right)_{1\le i,j\le n}$. The following steps are repeated until the stop condition is met:

- Each ant k constructs its complete solution $S_k$. If ant $k$ remains in node $i$, then node $j$ is probably chosen from a set of nodes that have not been visited, based on the heuristic function and on the pheromone at the edge ($i$ $j$);
- Each ant calculates $l_k$, the total length of its tour, and a local search procedure can be applied;
- The pheromone is increased at the transverse edges [34].

The Max-Min Ant System (MMAS) [43] can be seen as an interactive implementation of ML. MMAS brought three modifications to the AS and provided better results than the scalability of the point of view [43]: the edges in the best circumference from the current iteration get an additional amount of pheromones; at any given time, the pheromone at any edge belongs to the interval $[t_{min}, t_{max}]$; at the beginning, all edges receive the maximum amount of pheromones. MMAS is an elitist algorithm because it provides a pheromone update mechanism that favors edges that belong to the current best route: they are more likely to be selected in the next steps. It can be seen as a method of ML with external intervention, where the characteristics of the colony are corrected by not allowing excessive evaporation or excess pheromones at the edges. This makes it exploratory because all edges compete for passage [44].
The ant colony system (ACS) differs only in the calculation of the minimum number of pheromones from Ant-Q, however, the advantage is that it gives results of approximately the same quality, but much faster [45]. ACS introduces the following modifications to AS [46]: each ant selects the next node using a pseudo random proportional rule. At each step, only the pheromones on the best route are updated and before the iterations begin, each node has a list of candidates, in which the nearest neighbors are formed. When choosing the next step, the list of candidates is examined. Only if all nodes from the candidate list are visited, the algorithm starts checking other nodes. ACS can be viewed as a random elitist algorithm, where a random variable decides its elitist behavior. The list of candidates makes it faster, however strengthening the best route makes it less exploratory.
The learning of ants is similar to Monte Carlo trajectory sampling, i.e. ACO algorithms can be interpreted as a parallel replicated Monte Carlo system [47].
Three biologically inspired algorithms are used in the study [34] of TSP problem solving: AS, ACS and MMAS. The results were compared with those given by the LK method and it was concluded that empirical research shows that the variant that does not include learning with reinforcement has the least success. That is, the best variant among the considered ant algorithms is MMAS, because it learns quickly, is stable in repeated attempts and gives very good results.

### 4.3. Application of computational intelligence in the Vehicle Routing Problem

Vehicle routing has many practical applications in logistics, distribution, supply chain management and transportation. The Vehicle Routing Problem (VRP) is one of the most well-known combinatorial optimization problems, where the goal is to determine a set of routes with total minimum costs that can satisfy several geographically located nodes. A solution to this problem was proposed by Dantzig and Ramser in 1959. [48]. Since then, VRP has attracted the attention of a large number of researchers, as it analyzes many of the practical problems that distribution and transportation companies face on a daily basis. An example of a graphical representation of VRP is shown in Figure 2.

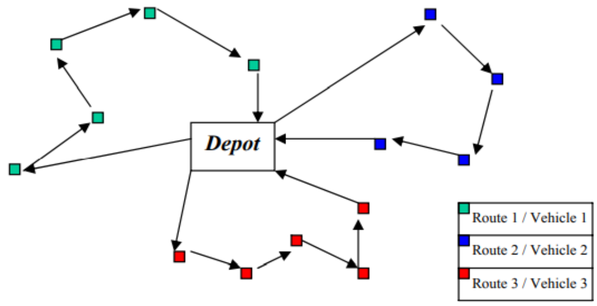


***Fig. 2*** *Graphical representation of VRP solution [49]*

Methods like branching and linking is the algorithm most commonly used in VRP. However, they are able to solve only small cases and therefore cannot be applied in practice, where there are a large number of limitations with a large number of users. Heuristic methods are then the most reliable and efficient approach to solving VRP, because they are able to provide high-quality approximate solutions in a reasonable time. Some VRP variants and their unique limitations [49] are:

- Capacitive vehicle routing problem (CVRP) is VRP with the additional restriction that all vehicles in the fleet have identical carrying capacity, and the goods along any route assigned to the vehicle must not exceed the vehicle capacity.
- Vehicle Routing Problem with Time Windows (VRPTV) is VRP with the additional restriction that each user or station has an associated, fixed time interval during which pickup or delivery must be performed.
- Capacitated Vehicle Routing Problem with Time Windows is hybrid version of CVRP and VRPTV.
- Multiple Depot Vehicle Routing Problem is VRP with multiple depots where, all stops must be assigned to a single depot or fleet in order to minimize service costs.
- Periodic Vehicle Routing Problem is VRP that enables service during M days, instead of one day realization.
- Split Delivery Vehicle Routing Problem is VRP in which individual users are serviced with more than one vehicle.
- Stochastic Vehicle Routing Problem is VRP in which there are one or more components that are random or present with a certain probability.

- Vehicle Routing Problem with Backhauls is VRP in which both pick-up and delivery can be performed at any station along the route.
- Vehicle Routing Problem with Satellite Facilities is VRP with the inclusion of remote objects in the entire transport network, which can be used to refuel or unload vehicles along their route.
- Time Dependent Vehicle Routing Problem is VRP where travel costs along the network depend on the time of day when the trip is to be realized.

Exponential growth in research, development and use of geographic information systems (GIS) has enabled GIS to address not only common spatial analysis problems, but complex spatial problems involving extremely large search spaces with correspondingly large numbers of potential solutions. In such cases, standard analytical techniques usually do not yield results, other than finding optimal solutions to problems within practical time and / or computational constraints. Such a problem in the field of spatial analysis is VRP. In order to optimize vehicle routing within GIS, it is important to apply two algorithms in the development of a paradigm in the field of CI. One is ACO, while the other is a genetic algorithm (GA) designed to develop optimal or near-optimal solutions to a problem using techniques based on natural selection, crossbreeding, and mutation [50]. The integration of these two algorithms is a hybrid metaheuristic algorithm for solving VRP, i.e. CVRP, which provides improved results from ACS [51].

Studies [52, 53] present a solution to the problem of routing vehicles with stochastic requirements, where a vehicle route is sought that connects all consumers to the depot, where the total distance is minimized and satisfies the condition that each consumer visits the depot - node once and that each route begins and ends in the same depot. Specific for this variant of VRP is that the design is done in uncertain only after the arrival of the vehicle in the node itself. Since random variables are stochastic quantities, the problem is solved using the heuristic and metaheuristic methods. Heuristic methods, in this case Clarke and Wright's saving algorithm, are used to construct routes, where the creation and improvement of the route is performed iteratively in relation to the goal function. While from the group of metaheuristic methods, local search 2-OPT [54] and simulated annealing algorithm [55].

### 4.4. Predicting the estimated time of arrival vehicles using machine learning

The Estimated time of arrival (ETA) is one of the conditions, because the demand in the node is known important parameters that need to be known in order to better plan transport. However, ETA is not easy to determine, especially for intermodal containerized freight transport, using multiple modes of transport. Operators need to increase the accuracy of the ETA in order to more efficiently allocate the human resources, equipment and space resources needed to meet the envisaged requirements. For decision makers, the processes associated with demand uncertainty can sometimes be very complex without the support of suitable methodological tools, as seen on Figure 4. ML is a good prediction model for intermodal freight transport networks (IFTN). For each stage of intermodal freight transport, an individual ML forecasting model is trained based on appropriate historical transport data and external data, such as processing times at logistics hubs and transport times by road and rail.

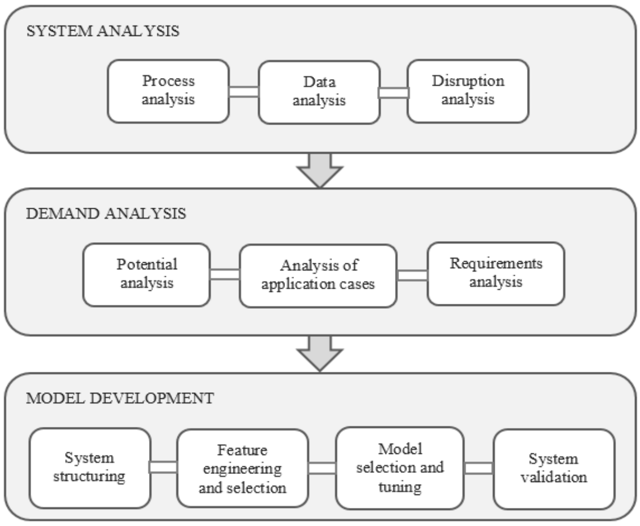


***Fig. 4*** *Application of research methods*

Based on the obtained results, decision makers are enabled to proactively resolve disturbances with the actors of the intermodal transport chain. Users can then initiate measures to combat potential critical delays in subsequent phases of transport. This approach leads to increased process efficiency for all actors in the implementation of complex transport operations and thus has a positive impact on the elasticity and profitability of IFTN. The model consists of the following steps: 1) structuring the system, 2) design features and selection of characteristics, 3) selection and adjustment of the model and 4) system validation. Figure 5 shows a schematic representation of the ETA for one mode of transport.

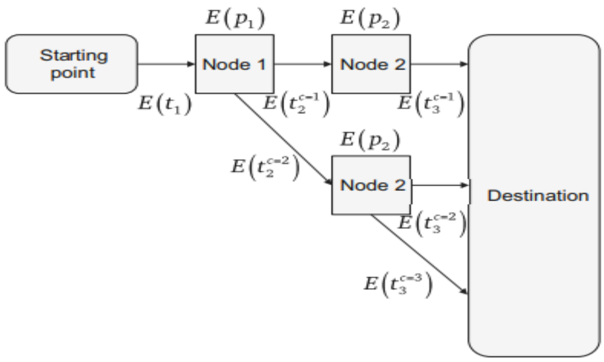


***Fig. 5*** *ETA scheme for one mode of transport [56]*

IFTN segments differ significantly in terms of operational constraints and data aspects, which is why all steps must be reported separately for each transport segment. Different technical approaches are implemented for each partial prediction model. A prediction model that estimates the transport time on the way between the sender and the internal terminal is a linear regression. Arrival time at the road terminal is based on "random forests". Random forest and gradient boosting are used to predict transport times for all sections of rail transport along the transport route from the inland terminal to the port. Ordinal forests are used to predict the time spent on the shunting train, with forecasting models trained on 70% of the available data and the remaining 30% of the data used to test the quality of the forecast [56].

## 5 CONCLUSION AND FUTURE DIRECTIONS FOR FURTHER RESEARCH

In this paper we have presented the techniques of CI and ML used in smart traffic and transport, emphasizing the fact that a large number of algorithms of CI and ML are ideal for exploiting a huge range of IoT data. The proposed algorithms can provide an efficient tool that assists operators in traffic and transportation management in real-time decision making with a large number of variables and control measures. In addition, the great progress that has already been made in the field of smart transport with the help of CI and ML has become obvious, while even better progress in this area is expected in the coming years. As the number of IoT devices increases, so does the diversity and number of data, so CI and ML can create many practical applications.

As the application of CI is applicable in different areas in future works, the application can be shown on the big data that exist in logistics and supply chains.

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