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Big Data Processing and Mining for the future ICT-based Smart Transportation Management System

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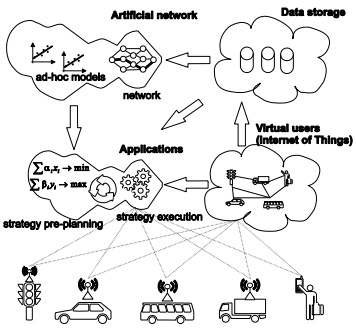
Graphical abstract



Abstract

Future Internet (FI) technologies can considerably enhance the effectiveness and user friendliness of present smart transportation management systems (STMS), providing considerable economic and social impact. Real-world application scenarios are needed to derive requirements for software architecture and smart functionalities of future-generation STMS in the context of the Internet of Things (IoT) and cloud technologies. The deployment of IoT technologies can provide future STMS with huge volumes of real-time data (Big Data) that need to be aggregated, communicated, analysed, and interpreted. In this study, we contend that future service- and cloud-based STMS can largely benefit from sophisticated data processing capabilities. Therefore, new distributed data mining and optimization techniques need to be developed and applied to support decision-making capabilities of future STMS. This study presents real-world scenarios of future STMS applications, and demonstrates the need for next-generation Big Data analysis and optimization strategies based on FI capabilities.

Keywords: Cloud computing architecture, ambient intelligence, distributed data processing and mining, multi-agent systems, distributed decision-making

1.0 INTRODUCTION

Increasing traffic and frequent congestion on today's roads require innovative solutions for infrastructure and traffic management. As the components of traffic systems become more autonomous and smarter (e.g. vehicles and infrastructure components are now equipped with communication capabilities), there is an increasing need for cooperation among intelligent transportation systems (ITS) for traffic management and environmental monitoring in order to improve traffic management strategies. Further, there is growing interest and increasing volume of investments to smart transportation management systems (STMS). In these new-generation business management systems, the management of transportation networks is closely integrated with the business strategies and operational models of transport companies and individual customers, providing a considerable impact for companies in terms of business planning, service quality and adaption to customer needs as well as for individual users in terms of time and money saving, adaptive travel planning and support of social mutually beneficial behaviour.

All participants of ITS act as data generators and sources, so there is a huge amount of available data with a short update rate. This growth in data production is being driven by: individuals and their increased use of media (social networks); infrastructure sensors; modern information and communication technologies (ICT) (*Modern mobile and communication technologies, Cloud computing, Internet of Things and Big Data Analytics, etc.*) with the proliferation of internet connected devices and systems. Data sets grow in size in part because they are increasingly being gathered by ubiquitous information-sensing mobile devices, aerial sensory technologies (remote sensing), software logs, cameras, microphones, radio-frequency identification readers, and wireless sensor networks. There has also been acceleration in the proportion of machine-generated and unstructured data (photos, videos, social media feeds and so on). One can speak about Big Data problem in STMS. Big Data usually includes data sets with sizes beyond the ability of commonly used software tools to capture, curate, manage, and process the data within a tolerable elapsed time. Big data supply more precise information about the customer, - but should be properly analysed in decentralized (multi-agent systems) manner without transmission of big information volumes,

therefore should be store and managed in cloud-based infrastructure and processed using cloud and grid computing capabilities.

Big data is decentralized (physically and logically) by its nature centralized virtually, which means that all information sources/storages are interconnected, and any piece of information can in principle be accessed by any component of the system. This distributed big data volumes (very often) created and managed in a decentralized fashion on the physical (fabric) layer. This raises the information costs that should be taken into account while accessing the information.

Thus, data mining and decision-making methods are required to find an optimal balance between decentralized information processing/decisions and costs of data transfer/decision coordination. This creates a need to employ innovative data mining and corresponding decision-making algorithms to support STMS applications in finding, collecting, aggregating, processing, and analysing information necessary for optimal decision-making user behaviour strategies.

Modern ICT technologies including cloud computing are developed to solve those problems in the more effective way. All of those approaches cannot solve these problems themselves and need the data volumes to be processed and big data processing and mining (BDMP) methods to be developed. Such methods help to store data in compact way (clustering) by dimension reduction finding rules in data behavior by predictive modeling, filtering and detecting outliners by change point analysis.

Innovative cloud services can be created using the cloud capabilities of future Internet (FI) to access smart objects via the Internet of Things (IoT). This development can enable wide access to necessary information, because all of this data will be available in-the-cloud. Cloud computing paradigm based on highly scalable computing resources, often configured as a distributed system, provides BDPM framework with big storage and fast computing capabilities. However, implementing a traffic cloud is far from easy. From an end user's point of view, the complexity of data and algorithms is hidden in the cloud. Users (ranging from traffic authorities to car drivers and automated components) expect to work with relatively simple applications on the Internet via mobile or embedded devices. These devices are fully connected and can (theoretically) use all the information available from all other users and system elements. This creates great opportunities for coordinated near-optimal management of the infrastructure (e.g. in terms of load balancing).

The contribution of this study is fourfold: First, we analyse related cloud-based architectures and STMS scenarios. Second, we consider architectures for implementing the corresponding data analysis and optimization of mobility operations. Third, we discuss the employment of appropriate mathematical methods for three use-cases; fourth, we point out and discuss work directions and opportunities in the area of cloud-enabled STMS.

The remainder of this paper is organized as follows. Section 2 reviews state of the art in the area of FI and cloud architecture for mobility application. In Section 3, we review Big Data data processing and mining (BDPM) methods application to STMS. In Section 4, we present a cloud-based data flow architecture for mobility networks. In Section 5, we propose and analyse three application scenarios of STMS and consider data analysis and optimization of participants' behaviour strategies in traffic systems. Section 6 contains experimental results. Section 7 concludes and discusses future research opportunities.

■2.0 STATE OF THE ART

2.1 Motivation and applications

A strong worldwide interest in opportunities in transportation and mobility field has spurred the need for further analysing these FI opportunities. In Europe, FI and IoT research has been a priority direction for the 7th European Framework Programme (FP7) and will continue to do so for the upcoming Horizon 2020 Programme (e.g. the objectives 'A reliable, smart and secure IoT for Smart Cities' or 'Integrated personal mobility for smart cities' in FP7 or 'Substantial improvements in the mobility of people and freight' in Horizon 2020). These research questions are motivated and co-funded by private companies and municipalities from the areas of transport, logistics, communication and traffic management (e.g. the FP7 project Instant Mobility [1]). These stakeholders understand the possible enhancements to existing systems that new technologies can provide to STMS. Research in this area is still largely at the stage of formulation of scenarios and coordination protocols.

In recent years, Big Data has become a major topic in the field of ICT worldwide. It is evident that Big Data means business opportunities, but also major research challenges. According to McKinsey & Co [45] and Gartner [46] Big Data is "the next frontier for innovation, competition and productivity". While US-based companies, including SMEs, are widely recognized for their activities in Big Data, very few research organizations, are known for their activities and initiatives in this field in Europe. Analytical Big Data services for SME's within Europe are currently non-existing. According to EU White papers [44], there are currently a number of initiatives aimed at adjusting the research landscape to lodge the rapid changes taking place in the processing of data under the current and seventh framework programme for Research and Innovation. There are a number of projects addressing a vast set of topics ranging from content creation and processing, "Big Data" analytics and real-time processing. In Horizon 2020, Big Data finds its place both in the Industrial Leadership, for example in the activity line "Content technologies and information management", and the Societal Challenges, relating to the need for structuring data in all sectors of the economy (health, climate, transport, energy, etc.). Not surprisingly, Big Data is also important to the Excellent Science priority of Horizon 2020, especially on scientific infrastructures and development of innovative high value added services.

STMS development is connected with Big data processing, therefore it is an important application domain for BDPM methods. Let us describe the STMS applications that are considered today as actual in the context of implementing FI technologies. First of all it is personal travel companion, which intends to provide to travellers, surface vehicle drivers and transports operators the benefits of dynamic planning and follow-up of multimodal journeys. The second very important problem considered by many authors is smart city logistics operations, which intends to provide benefits to actors and stakeholders involved in, affected by or dependent on the transportation of goods in urban environments.

2.2 Future ICT technologies

Future Internet (FI) technologies can enhance modern TMS and provide large-scale infrastructures for high-performance computing that are 'elastic' in nature, by adapting to user and application needs, [10].

Modern mobile and communication technologies such as wireless transmission, mobile Internet, mobile sensors as well as mobile devices (e.g. smart phones) serve as a good platform to the future generation of ITS. In recent years, vehicles are equipped with mobile devices with relatively powerful communication and processing capabilities as well as with sensors that provide various information about the environment. Constant Internet connection using 3G or 4G mobile Internet is nowadays usual and is favorable from price and quality point of view. This means that many traffic participants are already online and interconnected with rapidly growing trend; the problem is how to use this connection in order to provide efficient and reliable on-demand services to traffic participants.

Ambient intelligence (AmI) is a concept of interconnection of sensors and computational resources and using of artificial intelligence methods in order to improve everyday life. An architecture of AmI-enabled STMS is proposed in [8]. It supports virtual control strategists and management policy makers in decision-making and is modelled using the metaphor of autonomous agents. AmI is defined as the ability of the environment to sense, adapt, and respond to actions of persons and objects that inhabit its vicinity. Moreover, the multi-agent system (MAS) paradigm makes AmI environments act autonomously and socially, featuring collaboration, cooperation, and even competitive abilities. Other examples of AmI implementation are intelligent home or intelligent power grids.

MASs contain multiple autonomous self-interesting software entities, called agents. Agents percept information from the environment, create their own local data models and then make decisions according to their goals and available information. Decisions are then converted to actions, which influence the environment. Agents can interact and cooperate on the level of information models (data or model parameter exchange) or on the level of actions (action coordination, group formation). MASs provide a model of a system with intelligent behavior are a very good tool for the representation of complex distributed systems such as STMS.

Cloud computing systems are oriented towards a high level of interaction with their users, real-time execution of a large number of applications, and dynamic provisioning of on-demand services. In this study, we consider the layered architecture of cloud-based computing systems presented in [6]. It supports a class of specialized distributed systems that is characterized by a high level of scalability, service encapsulation, dynamic configuration, and delivery on demand. Beside that transport infrastructure can be considered as a service, which studies capabilities how to use FI technologies such as cloud data storage, cloud computing virtualization or services-in-the-cloud. The complexity of cloud-based systems is hidden from end users.

Agent-based cloud computing is a paradigm that identifies several common problems and provides several benefits by the synergy between MASs and cloud computing. Cloud computing is mainly focused on the efficient use of computing infrastructure through reduced cost, service delivery, data storage, scalable virtualization techniques, and energy efficiency. In contrast, MAS are focused on intelligent aspects of agent interaction and their use in developing complex applications. In particular, cloud computing can offer a very powerful, reliable, predictable and scalable computing infrastructure for the execution of MASs by implementing complex, agent-based applications for modeling and simulation. On the other hand, software agents can be used as basic components for implementing intelligence in clouds, making them more adaptive, flexible, and autonomic in resource management, service provisioning and large-scale application executions [10].

The Internet of Things (IoT) provides a new approach for virtual representation of the vehicles in the cloud-based STMS. It is a very important aspect for constructing of a cloud-based systems [12]. IoT semantically means a world-wide network of interconnected objects (radio frequency identification (RFID), infrared sensor (IR sensor), global positioning System (GPS), laser scanner, etc) uniquely addressable, that ensure the exchange and sharing of information in STMS. The basic idea of this concept is the pervasive presence around us of a variety of things or objects – such as (RFID) tags, sensors, actuators, mobile vehicles, etc. – which, through unique addressing schemes, are able to interact with each other and cooperate with their neighbors to reach common goals. The development of IoT based on Electronic Product Code (EPC) and RFID brings a good opportunity for STMS. At first, EPC assigns a unique electronic code for each traffic tool, ensuring the identification uniqueness for them similar to license plate. And then, RFID is a non-contact automatic identification technique and can identify traffic tools automatically and obtain related data via radio frequency signal. IoT provides for STMS two main things: 1) its data acquisition function provides more comprehensive traffic data; 2) provides a good channel for traffic data transmission. Therefore, STMS based on IoT has broad prospects of development and expansion space [12].

2.3 STMS architectures

The first cloud-based traffic network architectures have been proposed in [7], which employ ambient intelligence (AmI) [8] or IoT components [6], [7].

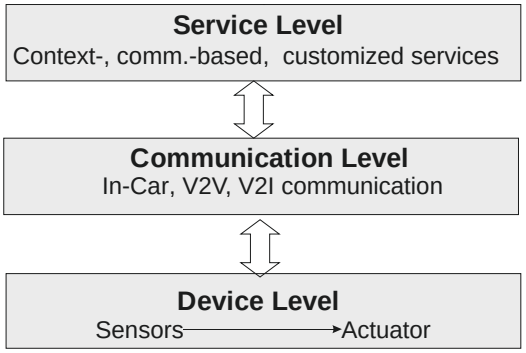


Figure 1 V-cloud architecture

V-cloud architecture was proposed in [9], which considers cloud computing in STMS from the point of device, communication and service level. It facilitates the interaction between vehicle drivers and outside car world, taking into account vehicle-to vehicle (V2V) and vehicle-to infrastructure (V2I) interactions to share and utilize external resources in a more effective way.

The architecture based on traditional cloud computing layer paradigm is considered in [7] (Figure 2).

The architecture (Figure 2) includes the following layers:

The **fabric** layer includes all computing, storage, data, and network resources available in the cloud. The resources are accessible through the resource services, are used for cloud computations, management, and as test beds.

The **unified** source layer provides infrastructure-as-a-service by defining unified access to the raw computational resources of the fabric layer using a virtual machine.

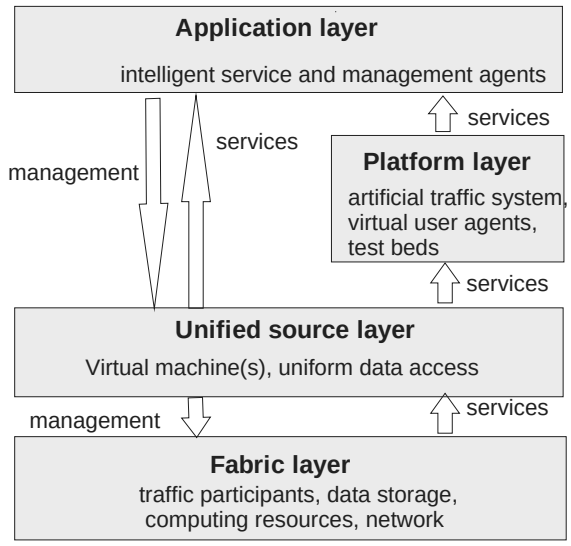


Figure 2 Cloud-based STMS architecture

The **platform** layer provides platform-as-a-service, including a collection of specialized tools, middleware, and services on the top of unified resources to create a deployment platform (e.g. scheduling create service and artificial test beds).

The application layer contains all applications that are run in the cloud. Application execution in the cloud is distributed: applications can be partly executed on the client, partly in the cloud.

The application of cloud-based architectures for STMS is demonstrated in [7]. In order to provide an acceptable level of service, a cloud-based STMS consists of two main components: an application component, which provides dynamic services and runs all the cloud applications; and a digital (simulated) traffic network component, which performs constant information collection and processing in order to provide in-time data. A cloud-based STMS adapts its decisions by using available information and by interacting with human as well as automated traffic participants.

The logical architecture of ICT-enable STMS was considered in [11], which data and computations can use traffic clouds. The research centres on the ACP (artificial, computational, parallel) approach. This approach involves modelling with artificial systems, analysis with computational experiments, and operation through parallel execution for control and management of complex systems with social and behavioural dimensions. They present an ACP -based framework that is a generalization of the feedback control mechanism in the control theory. The actual system and its artificial counterparts can be connected in various modes (learning and training, experimentation and evaluation, control and management) for different purposes (Figure 3). Artificial transportation system is developed to create a dynamic or 'living' ontology to present and organize transportation knowledge, such as methods, algorithms, regulations, and case studies, in a way that's effective for search and ready for computing and implementation. By comparing and analysing real and simulated behaviours, systems' future actions can be learned and predicted; control and management strategies for their operations can be accordingly planed and modified. The most interesting mode for our study is the Learning and Training mode. In this mode, the artificial systems serve mainly as a data centre for learning operational procedures and for training operators and administrators (Figure 4).

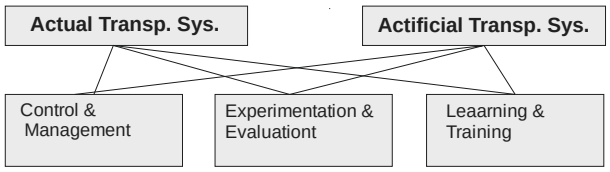


Figure 3 Another cloud-based STMS architecture

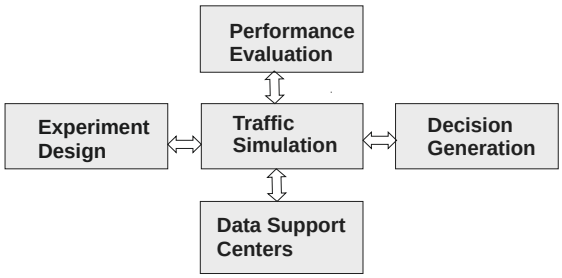


Figure 4 Architecture of the Learning and Training block

In [25] the following data processing stages in a typical cloud-based TMS are described. We applied our experience in implementing data processing, mining [3], [2], and decision-making methods [4], [5] for existing transportation problems. We present another BDPM oriented cloud-based STMS architecture.

■3.0 DDPM in STMS

The DDPM become one of the major research topics in information systems after the growth of the networks connectivity, and the data volume as well. Classical methods of data processing and mining are centralized: this means that in order to apply them, data should be available here and now. However it is not the case in modern information systems, including cloud-based STMS: huge volumes of data are collected in physically distributed storages, and it is not feasible or even impossible to collect all data in one place. Additional feature of data is its constant update. This means that there is an inherent need to develop effective BDPM algorithms that take into account space and time distribution of data. In the context of agent-based cloud computing, this problem is especially actual, as volumes of available distributed data rapidly grow.

3.1 DDPM methods

Analyzing and processing Big Data is now feasible both from a technical and cost perspective. Many big data frameworks are built around an understanding of business mechanics, analysis of the business strategy, identifying value and correlation in unstructured and structured data, data mining, predictive analysis and cost effective data [].Modern ICT technologies are developed to solve those problems in the more effective way. All of those approaches cannot solve these problems themselves and need the data volumes to be processed and big data processing and mining (BDMP) methods to be developed. Such methods help to store data in compact way (clustering) by dimension reduction finding rules in data behavior by predictive modeling, filtering and detecting

outliners by change point analysis. The BDPM methods on which the project is focused are listed below:

Regression analysis is a set of statistical techniques to determine how the value of the dependent variable changes when one or more independent variables are modified. The methods of regression analysis are the most widely used statistical tools for discovering the relationships among variables are often used for forecasting or prediction [47].

Time series analysis is the process of using statistical techniques to model and explain a time-dependent series of data points. Time series forecasting is the process of using a model to generate predictions (forecasts) for future events based on known past events. Time series data has a natural temporal ordering - this differs from typical data mining/machine learning applications where each data point is an independent example of the concept to be learned, and the ordering of data points within a data set does not matter […].

Cluster analysis is a statistical method for classifying objects that splits a diverse group into smaller groups of similar objects, whose characteristics of similarity are not known in advance. This is a type of unsupervised learning because training data are not used. This technique is in contrast to classification, a type of supervised learning […].

Classification is a set of techniques to identify the categories in which new data points belong, based on a training set containing data points that have already been categorized. These techniques are often described as supervised learning because of the existence of a training set; they stand in contrast to cluster analysis, a type of unsupervised learning [..].

Change-point analysis is a powerful new tool for *outliner detection* determining whether a change has taken place. It is capable of detecting subtle changes, it better characterizes the changes detected by providing confidence levels and confidence intervals. Change-point analysis is preferable processing historical data, especially when dealing with large data sets. A change-point analysis is powerful, well characterizes the changes, controls the overall error rate, is robust to outliers, is more flexible and is simpler to use […].

The BDMP become one of the major research topics in information systems after the growth of the networks connectivity. Classical methods of data processing and mining are centralized: this means that in order to apply them, data should be available here and now. In modern information systems Big Data are constantly updated and collected in physically distributed storages. Using the centralized approach the system cannot adapt quickly to situations in real time, and it is very difficult or simply impossible to transmit a large amount of information over the network and to store, manage and process large data sets in one location [15], [5]. In addition some nodes of the distributed system prefer relay mostly of their own experience in the prediction process. Therefore there is an inherent need to develop effective BDMP algorithms using decentralised architecture that take into account space and time distribution of data.

3.2 MAS in BDPM

Usually MAS represents a complex system, which consists of a large number of autonomous interacting components. Such systems are usually characterized by huge volumes of distributed data from various sources. One of the key challenges in MASs is the capability of agents to process and mine such distributed data in order to provide sufficient information for optimal decisions.

BDPM provides algorithmic solutions for data analysis in a distributed manner to detect hidden patterns in data and extract the knowledge necessary for decentralised decision-making [19], [20]. BDPM methods improve agent intelligence and MAS performance [21], involving pro-active and autonomous agents that perceive their environment, dynamically reason out actions on the basis of the environment, and interact with each other. Furthermore, the coupling of MAS with BDPM may be described in terms of ubiquitous intelligence [22], with the aim of fully embedding information processing into everyday life. This concept is very similar to the architecture of data clouds, where data and services are virtualised and provided on demand.

Some researchers describe a special type of agents that perform BDPM. Klusch at al. [23] concludes that autonomous data mining agents, as a special type of information agents, may perform various kinds of mining operations on behalf of their user(s) or in collaboration with other agents. Systems of cooperative information agents for data mining in distributed, heterogeneous, or homogeneous, and massive data environments appear to be quite a natural progression for the current systems to be realised in the near future.

Although the agents in MAS can be intelligent and powerful enough to perform data processing operations themselves. In many complex domains, the knowledge of agents is a result of the outcome of empirical data analysis in addition to the pre-existing domain knowledge. BDPM of agents often involves detecting hidden patterns, constructing predictive and clustering models, identifying outliers, etc. This collective ’intelligence’ of MAS must be developed by distributed domain knowledge and analysis of the distributed data observed by different agents. They collaborate to exchange knowledge that is extracted from data at different geographically distributed network nodes, creating as a result a distributed model of the environment – collective knowledge of the agents [21].

Usually MASs (not cloud computing MASs) represent a system, where communication is expensive and not possible between all nodes. So usually BDPM for MAS suppose computations with minimum network communication and maximum local computations, if possible. Local computation is carried out on each node, and either a central node communicates with each distributed node to compute the global models or a peer-to-peer (P2P) architecture is used. In the case of the P2P architecture, individual nodes might communicate with a resource-rich centralised node, but they perform most tasks by communicating with neighbouring nodes through message passing over an asynchronous network [21]. In our works we demonstrated that properly established distributed BDPM may provide almost the same quality of the models as centralized traditional methods.

<Typically, communication involves bottlenecks. Since communication is assumed to be carried out exclusively by message passing, the primary goal of several BDPM methods, as mentioned in the literature, is to minimise the number of messages sent. Building a monolithic database in order to perform non-distributed data processing and mining may be infeasible or simply impossible in many applications. The costs of transferring large blocks of data may be very expensive and result in very inefficient implementations [24].>

Following [13], the benefits of using MASs for BDPM are the following: 1) remaining the autonomy of data sources; 2) facilitating interactive BDPM; 3) improving dynamic selection of sources and data gathering; 4) having high scalability to massive distributed data; 5) stimulating multi-strategy BDPM; 6) enabling collaborative BDPM.

3.3 CC in DDPM

As we discussed above, cloud computing architecture is characterized by close integration of its users to the system and creating of their virtual representations in terms of IoT. As there is a large amount of data associated with each user and data is stored in the cloud, cloud computing systems automatically gets huge amounts of user data in the system. This data is used as source data and is initially natively distributed by users. However in contrast with the systems described in the previous section, the virtual users are fully connected and each piece of data can be accessed from other parts of the system.

The users of the cloud system usually have limited computational capacity because often they are connected to the cloud using mobile devices. So data processing is made by other agents, which collect information from users and store in the cloud. So the major issues of the BDPM are the workload and the communication cost. The implementing of cloud computing will handle a lots of this work load because of the high connectivity of these data agents/centres [14].

So the main difference between BDPM for "pure" MASs and for cloud computing is in dealing with communication. In the first case communication should be avoided if possible and was considered as a bottleneck. In the second case the communication is broadly available; the methods of BDPM for cloud computing should know *which information and where* is available. Instead of communication, the bottleneck is computation: usually more information is available that we are able to process. So another challenge is *quality* of the information: which one should be taken into account first.

This means that data processing and mining remains distributed when applied to cloud computing. However the question of the information availability will be replaced by a question of the information cost, which takes into account such factors as the information availability, speed of its extraction, quality, reliability, etc. This is why we call the methods of BDPM in cloud computing *semi-distributed (SBDPM):* they deal with information, which is physically distributed, but is available subject to costs.

Another challenge of SBDPM is *common* BDPM. There is a big number of cloud computing system users, which have similar but distinct requests to the cloud computing system. This means that BDPM should be done for similar characteristics (e.g. travel time) based on similar data in cloud computing system, however taking into account individual data and characteristics of user (e.g. its vehicle type and current route information). For this purpose, different levels of data processing should be done and characteristics pre-calculated and then they should be efficiently combined with actual user data.

The big challenge of the SBDPM is the parallelism use the calculation power to gain a precious time, the use of the cloud computing brings the ability of use many powerful interconnected servers with multi core processors without needing to implement it physically in every user's environment.

There are the following benefits of using SBDPM in cloud environments: 1) virtual integration of data sources into system without physical integration; 2) supporting availability of massive distributed data for BDPM; 3) facilitating cost-based selective BDPM; 4) stimulating multi-objective BDPM; 5) supporting multi-stage BDPM and different levels of data processing; 6) enabling common BDPM.

3.4 DDPM trend: Computational statistics

Cloud computing platform facilitates the data collection and provides the necessary resources for the operation of the computationally intensive methods of computational statistics.

Computational statistics is the interface between statistics and computer science. It is the area of computational science specific to the mathematical science of statistics. Computational statistics is aiming at the design of algorithm for implementing statistical methods on computers, including the ones unthinkable before the computer age (e.g. bootstrap, simulation), as well as to cope with analytically intractable problems.

The methods of computational statistics are modern methods, which are similar to the numerical methods for calculus [26]. Computational statistics supposes an application of iterative calculations instead of complex analytical models by using available data in different combinations. The resulting solution of the problem is approximate; however in many practical situations (small amount of available information, complex and hierarchical structure of analyzed system, dependency of data) this may give more robust and precise results as classical methods. On the other hand, computational statistics application is simple and does not require complex statistical procedures

The term computational statistics may also be used to refer to computationally intensive statistical methods including resampling methods, Markov chain Monte Carlo methods, local regression, kernel density estimation, artificial neural networks and generalized additive models.

3.5 Core methods and problems of DDPM

Centralized/decentralized architectures

Let us describe the core methods and problems of BDPM in traffic networks. In contemporary STMS, the modelling and forecasting of traffic flow is one of the important techniques that need to be developed [27]. It is a stochastic system in which a lot of different factors should be estimated.

Traffic information generally goes through the following three stages: data collection and cleansing, data fusion and integration, and data distribution. The system presented in [28] consists on three components, namely a Smart Traffic Agent, the Real-time Traffic Information Exchange Protocol and a centralised traffic information centre that acts as the backend.

There are several studies in which a centralised approach is used to predict the travelling time. The approach was used in various STMS, such as in-vehicle route guidance and advanced traffic management systems. A good overview is given in [29]. To make the approach effective, agents should cooperate with each other to achieve their common goal via so-called gossiping scenarios. The estimation of the actual travelling time using vehicle-to-vehicle communication without MAS architecture was described in [30].

There are a lot of disadvantages of the centralized approach. The system cannot adapt quickly to situations in real time, and it is very difficult or simply impossible to transmit a large amount of information over the network and to store and process large data sets in one location. In addition, it is known from practice that the most drivers rely mostly on their own experience; they use their historical data to forecast the travelling time [15], [5].

Thus, decentralised MASs with autonomous agents to allow vehicles to make decisions autonomously are fundamentally important for the representation of these networks [27].

A combination of centralized and decentralized agent-based approaches to the traffic control was presented in [35]. In this approach, the agents maintain and share the 'local weights' for each link and turn, exchanging this information with a centralized traffic information centre. The decentralised MAS approach for urban traffic network was considered in [34] also,

where the authors forecast the traversal time for each link of the network separately. Two types of agents were used for vehicles and links, and a neural network was used as the forecasting model.

We want to focus on the following problems of BDPM and demonstrate the advantages of decentralized architecture.

Travel time forecasting: Predictive models

Travelling time factor that plays an important role in transportation and logistics, and it can be applied in various fields and purposes. From travellers' viewpoints, the knowledge about travelling time helps to reduce the travelling time and improves reliability through better selection of travelling routes. In logistics, accurate travelling time estimation could help to reduce transport delivery costs and to increase the service quality of commercial delivery by delivering goods within the required time window by avoiding congested sections. For traffic managers, travelling time is an important index for traffic system operation efficiency [29].

A promising approach to agent-based parameter estimation for partially heterogeneous data in sensor networks was suggested in [33]. Another decentralised approach for homogeneous data was suggested in [31] to estimate the parameters of a wireless network by using a parametric linear model and stochastic approximations.

A problem of decentralised travel time forecasting was considered [2], [3], [18]. A MAS architecture with autonomous agents was implemented for this purpose. A decentralised linear [2], [18] and kernel density (KD) based [3], [18] multivariate regression models were developed to forecast the travelling time. The iterative least square estimation method was used for regression parameter estimation, which is suitable for streaming data processing. The resampling-based consensus method was suggested for coordinated adjustment of estimates between neighbouring agents. We illustrated the efficiency of the suggested approach using simulation with real data from the southern part of Hanover. The experiments show the efficiency of the proposed approach. The prediction technique in tutorial style was described in terms of distributed network intelligence in [18]. The comparison of parametric and non-parametric approaches for traffic-flow forecasting made in [39], shows the efficiency of the non-parametric KD regression

Clustering traffic states

A problem of clustering was considered. The CST KD-based methods were implemented [40], [41]. A MAS architecture with autonomous agents was implemented for this purpose. The resampling-based consensus method was suggested for coordinated adjustment of estimates between neighbouring agents. We illustrated the efficiency of the suggested approach using simulation with real data from the southern part of Hanover. The experiments show the efficiency of the proposed approach. The most popular clustering and classification problems in traffic research are traffic state clustering [32] and participant behaviour clustering for group formation [36]. Clustering of travel-time information trying to discover homogeneous traffic patterns to be used with the common forecasting model was discussed in [...]. A KD clustering [...], which is a promising non-parametric method of computational statistics tool and allows arbitrary shaped clusters to be discovered. Fast clustering, which is based on KD, was described by Hinnenburg and Gabriel [37]. The distributed (with a central authority) version of KD-based clustering (KDEC scheme) was considered in [23]. Another decentralised graph-oriented not KD clustering approach was presented in [38].

Change point analysis

Change Point Analysis for data processing and data mining of intelligent agents in city traffic was investigated [4]. The necessary agent-oriented architectures, scenarios and data flows were described [17]. Two CST-based resampling tests for change point detection were suggested, which were implemented at the DDM layer of agent logics. The efficiency of the suggested approach was evaluated [17] for two different scenarios based on real traffic data.

Traffic routing problem

A traffic routing problem with decentralized decision making of vehicle agents in urban traffic system was investigated, where the planning process for a vehicle agent is separated into two stages: strategic planning for selection of the optimal route and tactical planning for passing the current street in the optimal manner. A MAS architecture for this problem was developed [5], [15]; data flows and scenarios were analysed. Necessary CST-based BDPM algorithms for comparing two routes in a stochastic graph [5], [15], and the shortest path search were developed [16] which are carried out at strategic planning stage; the efficiency of the algorithms was evaluated. The models were implemented to real data and integrated into a traffic domain application use case. Experimental results show evidence for the efficiency of our approach.

■4.0 REFERENCE ARCHITECTURE FOR TRAFFIC CLOUD DATA PROCESSING AND MINING

In the previous Section we demonstrated technologies and BDPM methods used in cloud-based STMS. Now we demonstrate a sample architecture of a cloud-based STMS and explain the main data flows that occur there. We show as well how the data flows can be processed in order to implement SBDPM and provide sufficient information for fulfilling the user requests.

The applications executed in cloud are data-intensive. Services provided through the cloud require large amounts of data to be processed, aggregated, and analysed. Then, the processed data is used for calculating optimal strategies for traffic participants.

As we already mentioned, computation is a bottleneck in cloud computing. So a very important challenge of SBDPM is a reasonable processing balance between local data sources (clients) and a cloud. If a client has sufficient computational power, it can pre-process data locally and provide already processed data to the cloud, reducing cloud computations and network traffic. If however the computational power of a client does not allow information processing, the raw data are provided to the cloud and should be processed there. This is illustrated in Figure 5.

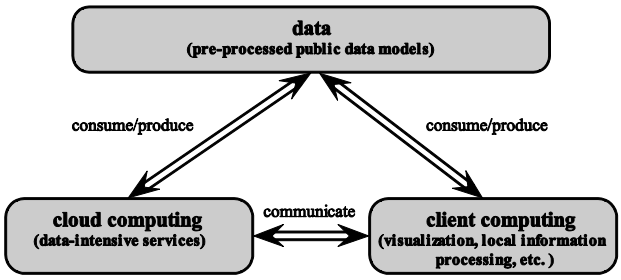


Figure 5 Data flow interconnections

Now we consider a reference architecture for traffic cloud data mining and optimization of strategies (TCDMOS), which is described in our previous works [] and based on [7]. In this architecture, we concentrate on illustrating data flows and their processing as well as using results for optimization of participant strategies and fulfilling their requests. A principal architecture of TCDMOS is illustrated in Figure 6.

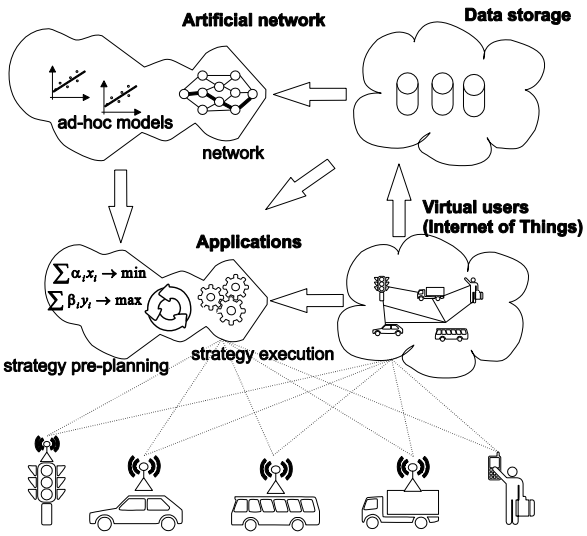


Figure 6 TCDMOS Architecture: Traffic Cloud Data Mining and Optimization of Strategies

It should be noted that there is not one cloud. There can be many clouds, made available from different providers. Some of the problems can be similar for them, and cooperation between them is possible.

The users of the TCDMOS (traffic participants such as vehicles or pedestrians, business users such as logistic providers, public transports or taxis, data providers such as cameras or detectors, as well as traffic managers such as traffic managements centers or traffic control elements) are connected with the cloud using stable and permanent Internet connection. This allows creating a virtual representation of each user in terms of IoT and having in the cloud dynamic sensor data, associated with them (pre-processed or raw). This creates a network of virtual users, which in fact is a mirror of reality in the cloud. This virtual reality contains distributed user data (partly stored in user devices, partly in the virtual storages provided by the cloud, but still associated with users). Note that disconnection of a user from the cloud does not mean elimination of its virtual representation; this only means that the locally stored data become unavailable for the cloud.

On the first stage data should be pre-processed. Raw sensor data requires very much storage space and cannot be stored for a long time. This data can be processed locally or upload to the cloud and pre-processed there. The results of the pre-processing are stored in the user profile and can be uploaded to the cloud at this stage.

The next very important stage is organizing of the virtual cloud information storages. This is made by cloud data mining agents, which collect the information, partially copying it to the storages in the cloud, partially making references to the user profiles, if they are available in the cloud. These agents put special attention to cost of the information, which includes its availability, reliability and precision. These virtual storages are subject of further SBDPM.

Cloud-based systems have a big number of users, and should fast react to their requests. For this purpose artificial ad-hoc networks are created, which are oriented to concrete problems, solved by the cloud system. For example, the networks oriented to shortest path calculation, traffic light regulation or passenger transit can be created.

There are two important problems solved in the artificial network: estimation of its parameters and pre-calculation of user strategies.

Estimation of the ad-hoc network parameters is the main stage of SBDPM. It consists in the estimation of the network parameters in order to obtain actual state of the network. Based on the information in the virtual storages estimation of the parameters is performed, taking costs of data into account and receiving data from physical storages if necessary. These parameters can be travel times on the network nodes, queues on the intersections or travel times between stops for public transport. A very important aspect is taking dynamic changes of the information into account, which is constantly provided by data mining agents.

Based on the estimated parameters pre-calculation

It includes the following stages of data processing and network optimization:

Stage 1: Mining data from the IoT and its pre-processing. All the participants of the cloud-based system have virtual representations as active IoT components (agents). These virtual agents are associated with data (mostly real-time) and act as data sources for the cloud-based system. The cloud system locates and collects the necessary data from different agents, and provides usual data mining operations (changes and outliers are detected, preliminary aggregation and dimensionality reduction are performed). The collected data are stored as historical information in the cloud and are used later as input data for ad-hoc network models (Stage 2). Stream-based methods of semi-decentralized change-point detection, outlier detection, clustering and classification, and factor analysis occur regularly in this stage.

Stage 2: Ad-hoc network models. The application-specific digital networks of virtual traffic participants (e.g. regional, social) are created, and the corresponding data models are used in order to estimate the important characteristics and parameters of these networks using the information collected in Stage 1 and for strategy optimization at Stage 3. The future behaviour of traffic participants is forecasted as well. Semi-decentralized, flows forecasting (possibly with incomplete information) methods such as (multiple-response) regression models, Bayesian networks, time series, simulation, are also applied at this stage. Many pre-defined data models can run concurrently in the digital network. The corresponding data storages are located in the cloud and are semi-centralized, so the methods should take costs of different pieces of information into account.

Stage 3: Static decisions and initial strategy optimization. Cloud applications use pre-calculated results of the ad-hoc network models from Stage 2 and the available historical information (including private information) about the traffic network to perform their pre-planning tasks. Initial optimization of the strategies is resource expensive, and can be partially pre-calculated in ad-hoc network models and then instantiated according to the application's goals and preferences. These models are also checked in the digital traffic network. This stage can require aggregation of different data models and existing strategies. Methods of self-learning stochastic (multi-criteria) optimization such as neural networks, decision trees, Markov decision processes, choice models, graph optimization algorithms are used.

Stage 4: Dynamic decisions and strategy update. The pre-planned tasks from Stage 3 are executed, and updates are made according to the dynamic real-time situation extracted from the virtual agents. The aggregation of the pre-planned data and strategies with the dynamic ones is the most important problem at this stage. An additional difficulty here is the requirement of fast real-time execution. (Automatic) cooperation between users in their decisions is possible; therefore, stream-based methods of data models and strategy updates such as reinforcement learning, Bayesian networks, dynamic decision trees, stream regression, and distributed constraint satisfaction/optimization can be applied.

■5.0 TRAFFIC CLOUD SCENARIOS

We propose three cloud-based STMS application scenarios: 1) A cooperative intersection control, which optimizes vehicle flows in traffic networks by regulating the intersection controllers. 2) A personal travel companion, which provides dynamic planning and monitoring of multimodal journeys to travellers, surface vehicle drivers, and transports operators. 3) A logistics services companion, which provides benefits to clients and stakeholders involved in, affected by, or dependent on the transportation of goods in urban environments. We demonstrate the most important stages of data processing and optimization in order to derive requirements for a general architecture described in the next section.

5.1 Virtualized cooperative intersection control

This scenario uses adaptive, semi-distributed traffic management strategies hosted in the cloud for the regulation of intersection controllers, and creates ad-hoc networks in the cloud between clusters of vehicles and the traffic management infrastructure. It recommends the optimal speed to drivers to keep the traffic flow smooth, and assists adapting traffic controllers (e.g. traffic lights, signs) based on the realtime traffic situation. This service uses real-time traffic information and a route-data collection service to formulate strategies for the optimization of network operation.

Stage 1: Processing the following data streams (historical and real-time): 1) floating-car data (speeds, positions, etc.); 2) sensor data from the infrastructure (loops, traffic lights, etc.); 3) information about routes and actual locations of collective transport (public transport, taxi, shared cars, etc.) 4) data from distribution vehicles (logistic transport); 5) weather conditions; 6) accidents, car breakdowns, road-works; 7) organizational activities (sport events, conferences, etc.)

Stage 2: Creating ad-hoc networks, which are virtual abstract networks for solving specific problems (intersection and regional traffic models, green wave models, public transport priority, jam avoidance, etc.). Estimating network parameters (traffic flux, density, and speed, travel time estimation, etc.).

Stage 3: Developing static strategies of intersection control and cooperation (such as increase of flows, changed weather conditions, organizational activities); cooperation plans of clusters of vehicles, etc.).

Stage 4: Combining dynamic real-time information with static strategies in order to receive up-to-date controlling decisions (correction of signal plans according to current conditions, cooperation of signal controllers to resolve problems such as jams, accidents, etc.) based on historical information, previous experience, and data models from the previous stage (traffic light signal plan optimization; signal plans for expected events

5.2 Dynamic multi-modal journey planning

The purpose of this use case is to help travellers plan and adjust a multi-modal, door-to-door journey in real-time. It provides improved (i.e., quicker, more comfortable, cheaper, and greener) mobility to daily commuters and other travellers by identifying optimal transportation means and a strong real-time orientation. This planning proposal for a multi-modal journey takes into account the current means of transportation, the traveller's context and preferences, city traffic rules, and the current requirements and constraints. The journey plan needs to obtain an overall indication of the trip duration as well as accommodate early reservation of resources (train or plane ticket).

Stage 1: Processing of the following data streams (historical and dynamic) in addition to the previous application: 1) floating passenger data; 2) travellers' preferences; 3) timetables and availability of collective transport (tickets, shared cars availability, etc.); 4) changes in time-tables.

Stage 2: Creation of ad-hoc networks (transit stations, public transport coordination, passenger choice of transport, etc.) and estimation of network parameters (travel time for different transport modes depending on various factors, waiting times, passenger arrival at stops, price models, etc.).

Stage 3: Multi-modal route pre-planning based on historical data and estimated network parameters for expected conditions (pre-planning for popular routes, preplanning for pre-booked routes, pre-planning for expected events) as well as optimal time-table calculation for public transport based on the expected conditions.

Stage 4: Dynamic update of pre-planned routes for the actual multi-modal journey (actual travel-time estimation, re-planning in the case of delays in previous trips in the multi-modal chain, re-planning for additional travel possibilities, or cancelling a part of the multi-modal journey), as well as dynamic update of public transport time-tables (on-demand changes, co-ordination of different transport means).

5.3 Itinerary booking and real-time optimized route navigation

This use case helps a logistics provider (1) guarantee quick (especially on-time) deliveries at a low cost based on up-to-date information and (2) maximize the efficiency of each vehicle and the fleet. It is fundamental to optimize the movements of the logistics vehicles, to help them avoid traffic jams and take the shortest routes when possible.

Stage 1: Processing of the following data streams (historical and dynamic) in addition to the first application: 1) order data (transportation demand); 2) available logistic vehicles (possible load, speed, etc.); 3) timetables (if necessary) and actual positions of the vehicles; 4) client data (drop-off preferences, actual location, etc.).

Stage 2: Creation of ad-hoc networks (delivery models, logistic provider-client interaction models, etc.), and estimation of the network parameters (travel times for different route segments, delay probability, drop-off process time distribution, probability of accidents, probability of problems with vehicles, etc.).

Stage 3: Pre-planning of the delivery process (preliminary good distribution by vehicles, preliminary order of clients for each vehicle, preliminary route for each vehicle, preliminary time window for each client, etc.). Note that the itineraries of large logistic operators can be used to provide better predictions of the traffic situation using virtualized cooperative intersection

intelligence application as well as by applying priority rules for logistic vehicles during booking.

Stage 4: Dynamic update of pre-planned delivery routes depending on up-to-date information (re-planning of routes depending on current traffic situation, re-planning in the case of accidents or traffic jams, re-planning in the case of vehicle problems, estimation of actual delivery time, etc.). Cooperation between logistic vehicles (exchange or orders, adoption of other vehicle's orders in the case of problems, etc.). Dynamic agreement with clients (agreement about drop-off place depending on current position of the vehicle and client, agreement about change of drop-off time, reaction to the new/changed customer requests, etc.).

■6.0 METHODS OF BDPM IN CLOUD-BASED STMS

In this Chapter we provide an overview of two very important groups of BDPM methods, which can be applied in cloud-based environments: *decentralised clustering*, which groups together similar data and *decentralised regression*, which provides estimation of some characteristics depending on given values of factors. Both methods are distributed, which allows combination of local and global computations, which provides a very good basis for their application in cloud context.

6.1 Decentralised regression

Regression analysis models the dependency between the dependent variable (usually denoted by **Y**) and independent variables (factors, usually denoted by **X**). It describes the dependence of conditional expectation $E[\boldsymbol{Y}|\boldsymbol{X}]$ on the values of several independent variables (factors) **X**.

A *linear regression* model supposes that the dependent variable **Y** is a linear combination of the factors **X**. The linear regression model in the matrix form can be expressed as

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{6.1}$$

where $\mathbf{Y}$ is an $n \times 1$ vector of dependent variables; $\mathbf{X}$ is an $n \times d$ matrix of explanatory (dependent) variables; $\boldsymbol{\beta}$ is an $d \times 1$ vector of unknown coefficients, which are parameters of the system to be estimated; $\boldsymbol{\varepsilon}$ is an $n \times 1$ vector of random errors. The rows of the matrix $\mathbf{X}$ correspond to observations and the columns correspond to factors.

The well-known least square estimator (LSE) $\mathbf{b}$ of $\boldsymbol{\beta}$ is:

$$\mathbf{b} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y}. \tag{6.2}$$

After the estimation of the parameters $\boldsymbol{\beta}$, we make a forecast for a certain t-th future values of the factors $\mathbf{x}_t$:

$$E[Y_t] = \mathbf{x}_t\mathbf{b}. \tag{6.3}$$

A *KD regression* model does not make certain assumptions about the form of dependence of dependent variable **Y** on factors **X**. It can predict observations without reference to a fixed parametric model. It uses kernel as a weighting function in the estimation process.

A general form of a non-parametric regression model is:

$$\mathbf{Y} = m(\mathbf{x}) + \boldsymbol{\varepsilon}, \tag{6.4}$$

where $\boldsymbol{\varepsilon}$ is a random error such that $\mathrm{E}[\boldsymbol{\varepsilon} \mid \mathbf{X} = \mathbf{x}] = \mathbf{0}$ and $\mathrm{Var}[\boldsymbol{\varepsilon} \mid \mathbf{X} = \mathbf{x}] = \sigma^2(\mathbf{x})$; and $m(\mathbf{x}) = \mathrm{E}[\mathbf{Y} \mid \mathbf{X} = \mathbf{x}]$.

The Nadaraya-Watson KD estimator is

$$\widehat{m}_n(\mathbf{x}) = \frac{\sum_{i=1}^n H^{-1}K(\mathbf{x}-\mathbf{X}_i)\,Y_i}{\sum_{i=1}^n H^{-1}K(\mathbf{x}-\mathbf{X}_i)} = \frac{\sum_{i=1}^n \omega_i(\mathbf{x})\,Y_i}{\sum_{i=1}^n \omega_i} = \\ = \sum_{i=1}^n \widehat{\omega}_i(\mathbf{x})Y_i, \tag{6.5}$$

where $K(\bullet)$ is the kernel function of R^d, H is the bandwidth matrix, $\omega_i(\mathbf{x}) = K\left(\frac{\mathbf{x}-\mathbf{X}_i}{h}\right)$ are the weights of the historical observations in the forecast of $\mathbf{x}$ and , $\widehat{\omega}_i(\mathbf{x}) = \frac{\omega_i(\mathbf{x})}{\sum_{i=1}^n \omega_i}$ are the corresponding normalised weights. If there is no additional information about factor dependence, $\mathbf{H} = diag(h_1, h_2, \ldots, h_d)$. Kernel function is a symmetric density function, for example a standard miultivariate normal distribution $\mathbb{N}(0, I)$, called the multivariate Gaussian kernel.

Using the Nadaraya-Watson estimator, a forecast for any future factors $\mathbf{x}_{n+1}$ can be made:

$$E[Y_{n+1}] = \widehat{m}_n(\mathbf{x}_{n+1}). \tag{6.6}$$

Now we consider *distributed versions* of the above-mentioned linear and KD regressions. The main idea is that each agent makes estimations of its models locally based on its observations; in the case of difficulties it asks for a help from other agents and receives the model parameters (e.g. in the case of linear regression) or raw data (e.g. in the case of kernel regression), which are used to improve initial model.

Suppose we have a MAS consisting of s autonomous agents $\boldsymbol{Ag} = \{Ag^{(1)}, Ag^{(2)}, \ldots, Ag^{(s)}\}$, and each of them contains a local regression model, which is estimated on the basis of its experience. We now introduce a parameter adjustment algorithm, which allows the agents to exchange their model parameters in order to improve the forecasts.

Consider an agent $Ag^{(i)}$ which makes a forecasting for some factors $\mathbf{x}_{t+1}^{(i)}$ using linear or KD regression**.** After forecasting, $Ag^{(i)}$ checks whether it needs help from other agents. This is done when the agent considers a forecast $E\left[Y_{t+1}^{(i)}\right]$ as not reliable.

For the linear model, an approach to check a reliability of a forecast is to compare the width of the confidence interval of the forecast with a forecast value. The forecast $E\left[Y_{t+1}^{(i)}\right]$ is considered to be not reliable if its value is sufficiently smaller than its confidence interval width:

$$\frac{\Delta^{(i)}(\mathbf{x}_{n+1}^{(i)})}{\mathbf{x}_{n+1}^{(i)}\mathbf{b}_t^{(i)}} > p,$$

where p is an agent's parameter representing the maximal ratio of the confidence interval width to the forecast, after which a coordination takes place; $\Delta^{(i)}(\mathbf{x}_{t+1}^{(i)})$ is the confidence interval for factors $\mathbf{x}_{t+1}^{(i)}$ based on the agent's data.

For the KD model, we consider a forecast for $\mathbf{x}_{n+1}^{(i)}$ as not reliable if only one of the observations is taken with a significant weight in this forecast:

$$\max\left(\widehat{\omega}_c^{(i)}\left(\mathbf{x}_{n+1}^{(i)}\right)\right) > bp,$$

where bp is a is an agent's parameter representing the maximal weight, after which a coordination takes place.

Now, let us describe the parameter adjustment procedure, in which agent $Ag^{(i)}$ sends first a request to other agents within its transmission radius. This request contains a set of factors $\mathbf{x}_{n+1}^{(i)}$ as well as a threshold $Tr^{(i)}\left(\mathbf{x}_{n+1}^{(i)}\right)$.

For the linear model this threshold is set equal to the confidence interval width: $Tr^{(i)}\left(\mathbf{x}_{n+1}^{(i)}\right) = \Delta^{(i)}\left(\mathbf{x}_{t+1}^{(i)}\right)$.

For the KD model this threshold for the observation weight is set as the weight of the second best observation: $Tr^{(i)}\left(\mathbf{x}_{n+1}^{(i)}\right) = \omega_{(n-1)}^{(i)}\left(\mathbf{x}_{n+1}^{(i)}\right)$, where an ordered sequence of weights in the forecast for $\mathbf{x}_{t+1}^{(i)}$ is represented by $\omega_{(1)}^{(i)}\left(\mathbf{x}_{t+1}^{(i)}\right), \omega_{(2)}^{(i)}\left(\mathbf{x}_{t+1}^{(i)}\right), \dots, \omega_{(n)}^{(i)}\left(\mathbf{x}_{t+1}^{(i)}\right)$.

Each agent $Ag^{(j)}$ in the transmission radius after the receiving of data makes the following.

For the linear model it calculates the confidence interval $\Delta^{(j)}(\mathbf{x}_{n+1}^{(i)})$ for the requested values of factors $\mathbf{x}_{n+1}^{(i)}$ on the basis of its data and compares it with the threshold. If this value is less than the threshold, $\Delta^{(j)}\left(\mathbf{x}_{t+1}^{(i)}\right) < Tr^{(i)}\left(\mathbf{x}_{t+1}^{(i)}\right)$, $Ag^{(j)}$ replies to $Ag^{(i)}$ by sending its parameters $\mathbf{b}_t^{(j)}$.

For the KD model it calculates the weights $\omega_c^{(j)}\left(\mathbf{x}_{n+1}^{(i)}\right)$ on the basis of its own data. If there are observations with weights$\omega_c^{(j)}\left(\mathbf{x}_{n+1}^{(i)}\right) > Tr^{(i)}\left(\mathbf{x}_{n+1}^{(i)}\right)$ it forms a reply $\widehat{D}^{(j,i)}$ from these observations (maximum 2) and sends it to $Ag^{(i)}$.

Let us define $G^{(i)} \subset \boldsymbol{Ag}$, as a group of agents, who are able to reply to $Ag^{(i)}$ by sending the requested data.

For the linear model each $Ag^{(j)}$ sends its parameters $\mathbf{b}_n^{(j)}$. $Ag^{(i)}$ receives replies from the group $G^{(i)}$. It assigns weights to each $Ag^{(j)} \in G^{(i)}$ (including itself) $c^{(i)}=\left\{c_j^{(i)}\right\}$; these weights are time-varying and represent the reliability level of each $Ag^{(j)}$ (including reliability of own experience). In our case, the agents' weights depend on the forecasting experience. According to the logic of constructing discrete-time consensus, we assume that $c^{(i)}$ is a stochastic vector for all t (the sum of its elements is equal to 1). Then an updated estimate $\tilde{\mathbf{b}}_{\mathrm{t}+1}^{(i)}$ is calculated as

$$\tilde{\mathbf{b}}_{\mathrm{t}+1}^{(i)} = \sum_{Ag^{(j)} \in G^{(i)}} c_j^{(i)}\, \mathbf{b}_t^{(j)} \tag{6.7}$$

For the KD model the agents $Ag^{(j)}$ send their data, which are closest to the requested point. All the data $\widehat{D}^{(j,i)}$, $Ag^{(j)} \in G^{(i)}$ received by $Ag^{(i)}$ are verified and duplicated data are discarded. These new observations are added to the dataset of $Ag^{(i)}$: $D^{(j)} \leftarrow \bigcup_{Ag^{(j)} \in G^{(i)}} \widehat{D}^{(j,i)} \cup D^{(j)}$. Suppose that $Ag^{(i)}$ received r observations. Then, the new KD function of $Ag^{(i)}$ is updated by considering the additive nature of this function:

$$\widetilde{m}_{n+r}^{(i)}(\mathbf{x}) = \frac{p_n^{(i)}(\mathbf{x}) + \sum_{Ag^{(j)} \in G^{(i)}} p^{(i,j)}(\mathbf{x})}{q_n^{(i)}(\mathbf{x}) + \sum_{Ag^{(j)} \in G^{(i)}} q^{(i,j)}(\mathbf{x})}, \tag{6.8}$$

where $p^{(i,j)}(\mathbf{x})$ and $q^{(i,j)}(\mathbf{x})$ are the nominator and denominator of (6.5), respectively, calculated by $\widehat{D}^{(j,i)}$. Finally, $Ag^{(i)}$ can autonomously make its forecast for $\mathbf{x}_{n+1}^{(i)}$ as $\widetilde{m}_{n+r}^{(i)}(\mathbf{x}_{n+1}^{(i)})$.

6.1 Decentralised clustering

We formulate first the clustering problem and describe the KD clustering algorithm. Let $\boldsymbol{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N\}$, $\boldsymbol{x}_i \in R^d$ be a dataset to be clustered into k non-overlapping subsets $S_1, S_2, \dots, S_k, \}$.

Non-parametric clustering methods are well suited for exploring clusters without building a generative model of the data. KD clustering consists of a two-step procedure: estimation and optimisation. During the estimation step, the probability density of the data space is directly estimated from data instances. During the optimisation step, a search is performed for densely populated regions in the estimated probability density function.

Estimation step. The density function is estimated by defining the density at any data object as being proportional to a weighted sum of all objects in the data-set, where the weights are defined by an appropriately chosen kernel function [23].

A KD estimator is

$$\hat{\psi}^{[\boldsymbol{X}]}(x) = \frac{1}{N} \sum_{x_i \in \boldsymbol{X}} K_H(\|x - x_i\|), \tag{6.8}$$

where $\|x - x_i\|$ is a distance between x_i and x, $K_H(\bullet) = |H|^{-1} K(H^{-1}\bullet)$[42]. We use the multivariate Gaussian kernel function in our study: $K(\mathrm{x}) = (2\pi)^{-d/2}\exp(-\frac{1}{2}\boldsymbol{x}^T\boldsymbol{x})$.

Optimisation step. Maxima of KD are detected and groups all of the data objects in their neighbourhood are grouped into corresponding clusters. We use a hill climbing method for KD maxima estimation with Gaussian kernels (DENCLUE2) [37] and modify the technique for the multivariate case. This method converges towards a local maximum and adjusts the step size automatically at no additional costs. Other optimization methods [37] require more steps and additional computations for step size detection. Each KD maximum can be considered as the centre of a point cluster. With centre-defined clusters, every local maximum of $\hat{\psi}(\bullet)$ corresponds to a cluster that includes all data objects that can be connected to the maximum by a continuous, uphill path in the function of $\hat{\psi}(\bullet)$. Such centre-defined clusters allows for arbitrary-shaped clusters to be detected, including non-linear clusters. An arbitrary-shape cluster is the union of centre-defined clusters that have maxima that can be connected by a continuous, uphill path. The goal of the hill climbing procedure is to maximize the KD $\hat{\psi}^{[\boldsymbol{X}]}(x)$. By setting the gradient $\nabla\hat{\psi}^{[\boldsymbol{X}]}(x)$ of KD to zero and solving the equation $\nabla\hat{\psi}^{[\boldsymbol{X}]}(x) = \mathbf{0}$ for x, we get:

$$\boldsymbol{x}^{(l+1)} = \frac{\sum_{x_i \in \boldsymbol{X}} K_{\boldsymbol{H}}(\|\boldsymbol{x}^{(l)} - \boldsymbol{x}_i\|)\boldsymbol{x}_i}{\sum_{x_i \in \boldsymbol{X}} K_{\boldsymbol{H}}(\|\boldsymbol{x}^{(l)} - \boldsymbol{x}_i\|)}, \tag{6.9}$$

The formula (6.9) can be interpreted as a normalized and weighted average of the data points. The weights for each data point depend on the influence of the corresponding kernels on $\boldsymbol{x}^{(l)}$. Hill climbing is initiated at each data point $\boldsymbol{x}_i \in \boldsymbol{X}$ and is iterated until the density does not change, i.e. $\left[\hat{\psi}^{[\boldsymbol{X}]}\left(\boldsymbol{x}_i^{(l)}\right) - \hat{\psi}^{[\boldsymbol{X}]}\left(\boldsymbol{x}_i^{(l-1)}\right)\right] / \hat{\psi}^{[\boldsymbol{X}]}\left(\boldsymbol{x}_i^{(l)}\right) \le \boldsymbol{\epsilon}$, where $\boldsymbol{\epsilon}$ is a small constant. The end point of the hill climbing algorithm is denoted by $\boldsymbol{x}_i^* = \boldsymbol{x}_i^{(l)}$, corresponding to a local maximum of KD.

Now we should determine a cluster for $\boldsymbol{x}_i$. Let $\boldsymbol{X}^c = \{\boldsymbol{x}_1^c, \boldsymbol{x}_2^c, \dots\}$ be an ordered set of already identified cluster centres (initially, we suppose $\boldsymbol{X}^c \neq \emptyset$). First we find an index of the nearest cluster centre from $\boldsymbol{x}_i^*$ in the set $\boldsymbol{X}^c$:

$$nc(\boldsymbol{x}_i^*) = \arg min_{\boldsymbol{x}_j^c \in \boldsymbol{X}^c} \|\boldsymbol{x}_j^c - \boldsymbol{x}_i^*\|.$$

We describe now the cooperation for sharing the clustering experience among the agents in a network. While working with

streaming data, one should take into account two main facts. The nodes should coordinate their clustering experience over some previous sampling period and adapt quickly to the changes in the streaming data, without waiting for the next coordination action.

Let us first discuss the cooperation technique. We introduce the following definitions. Let $\boldsymbol{Ag} = \{Ag^{(1)}, Ag^{(2)}, \dots, Ag^{(p)}\}$, be a group of p agents. Each $Ag^{(j)}$ has a local dataset $D^j = \{x_t^j | t = 1, \dots, N^j\}$, where $\boldsymbol{x}_t^j \in R^d$. In order to underline the dependence of the KD function (6.8) on the local dataset of $Ag^{(j)}$, we denote the KD function by $\hat{\psi}^{[\boldsymbol{D}^j]}(\boldsymbol{x})$.

Consider a case when some agent $Ag^{(i)}$ is unable to classify (after optimization has formed a new or small cluster) some future data point $\boldsymbol{x}_t^i$ because it does not have sufficient data in the neighbourhood of this point. Our model uses a two-phase protocol for performing communication between agents. Agent $Ag^{(i)}$ sends the data point $\boldsymbol{x}_t^i$ to the other neighbouring agents.

We consider two different helping procedures: non-parametric, in which some data are transmitted, no parameter estimation is performed and semi-parametric, where the observations are approximated with the mixture of multivariate normal distributions and their parameters are transmitted.

In the non-parametric procedure, considered in […], each of $Ag^{(j)}$ that has received the request classifies $\boldsymbol{x}_t^i$ using its own KD function $\hat{\psi}^{[\boldsymbol{D}^j]}(\boldsymbol{x}_t^i)$ and performs the optimization step to identify the cluster for this point. Let $n_{j,i}$ be a number of points in the cluster of $\boldsymbol{x}_t^i$, not including $\boldsymbol{x}_t^i$, itself. In the case of successful clustering ($n_{j,i} > 0$), of $Ag^{(j)}$ forms an answer $\boldsymbol{D}^{j,i}$ with c nearest points to the requested data point from the same cluster as $\boldsymbol{x}_t^i$, (or all points from the cluster, if $n_{j,i} \leq$ c. Let $c_{j,i}$ be a number of points in the answer $\boldsymbol{D}^{j,i}$. The agent of $Ag^{(j)}$ sends $\boldsymbol{D}^{j,i}$together with $c_{j,i}$ and $n_{j,i}$ to of $Ag^{(i)}$. After receiving all the answers, $Ag^{(i)}$ forms a new dataset $\widehat{\boldsymbol{D}}^{j,i}$.

In the semi-parametric procedure, considered in […], in response to the help-request, the neighbours of $Ag^{(j)}$ send parameters from their estimated KD functions. Since the KD function is non-parametric and estimated directly from observations, we approximate the function with a mixture of multi-dimensional Gaussian distributions. Agent of $Ag^{(j)}$ identifies cluster associated with point $\boldsymbol{x}_t^i$ and performs the approximation of clusters with a mixture of normal distributions. Next, of $Ag^{(j)}$ transmits the cluster parameters (weight, mean and covariance matrix). The agent of $Ag^{(i)}$ adds this information to its KD and updates its clusters. Since

After updating its KD function, of $Ag^{(i)}$ can perform a hill-climbing optimization procedure to identify clusters in its local data space.

parameter transmission requires less data, this approach requires less transmission, however, the approximation reduces the cluster shapes to a union of ellipsoids.

Let us consider an approximation step that approximates KD functions with a mixture of multivariate normal distributions. This step can be achieved with the expectation maximisation (EM) algorithm proposed by Dempster [43]. The approach is widely used for calculation of the maximum likelihood estimate of mixture models. In a mixture model, the probability density function is

$$f(\boldsymbol{x}; \Theta) = \sum_{b=1}^{B} \pi_b f_b(\boldsymbol{x}; \Theta_b),$$

where π_b are positive mixing weights that sum to one, f_b are component density functions parameterized by Θ_b, and $\Theta = \{\pi_b, \Theta_b\}$ are the model parameters. Each observation is assumed to be from one of the B components. A common choice for component density is a multivariate normal distribution with parameters $\Theta_b = (\mu_b, \Sigma_b)$, where μ_b is a mean and Σ_b is a covariance matrix.

In the EM procedure, the expected likelihood of a given data-set is iteratively maximized. The algorithm [43] alternates between the E and the M steps until convergence is achieved.

We assume that each helping-agent $Ag^{(j)} \in \boldsymbol{G}^{(l)}$ receives data point $\boldsymbol{x}_t^i$ and tries to classify it. If it is successful, of $Ag^{(j)}$ determines that $\boldsymbol{x}_t^i$ belongs to a specific cluster and executes the EM-algorithm with this cluster. This algorithm approximates the cluster using a mixture of B^j multidimensional normal distributions with parameters $\Theta^j = \{\mu^j, \Sigma^j, \pi^j\}$, where $\mu^j = \{\mu_1^j, \dots, \mu_{B^j}^j\}$, $\Sigma^j = \{\Sigma_1^j, \dots, \Sigma_{B^j}^j\}$, and $\pi^j = \{\pi_1^j, \dots, \pi_{B^j}^j\}$, which are then returned to $Ag^{(i)}$. After receiving all answers, the agent Ai has a vector of the parameters $\{\Theta^j\}$. The answers $\{\Theta^j\}$ can be interpreted by the agent $Ag^{(i)}$ as data points μ^j with the only difference being that the additional weights π^j and bandwidths from Σ^j should now be taken into account.

The next problem is the updating of the KD function of $Ag^{(i)}$. Denote $\widehat{\boldsymbol{D}}^i$as a dataset of the agent of $Ag^{(i)}$ that includes the received answers. We take into account that density estimates (6.8) of each agent are additive, i.e. the aggregated density estimate $\hat{\psi}^{[\boldsymbol{D}^j]}(\boldsymbol{x})$ can be decomposed into the sum of the local density estimates.

For the non-parametric approach $\hat{\psi}^{[\boldsymbol{D}^j]}(\boldsymbol{x})$ is updated with respect to the new knowledge $\boldsymbol{D}^{j,i}$ with one estimate for every dataset $\boldsymbol{D}^{j,i}$:

$$\hat{\psi}^{[\widehat{\boldsymbol{D}}^i]}(\boldsymbol{x}) = \\ = w_i \hat{\psi}^{[\boldsymbol{D}^i]}(\boldsymbol{x}) + \frac{(1 - w_i)}{\sum_{Ag^{(j)} \in \boldsymbol{G}^{(i)}} n_{j,i}} \sum_{Ag^{(j)} \in \boldsymbol{G}^{(i)}} n_{j,i}\, \hat{\psi}^{[\boldsymbol{D}^{j,i}]}(\boldsymbol{x}), \qquad (6.10)$$

where w_i is a weight used for the agent's own local observations.

For the semi-parametric procedure it uses the estimated parameters

$$\hat{\psi}^{[\widehat{\boldsymbol{D}}^i]}(\boldsymbol{x}) = w_i \hat{\psi}^{[\boldsymbol{D}^i]}(\boldsymbol{x}) + \\ + \frac{(1-w_i)}{\sum_{\substack{Ag^{(j)} \in \boldsymbol{G}^{(i)} \\ b \in B^j}} \pi_b^j \sum_{Ag^{(j)} \in \boldsymbol{G}^{(i)}} B^j} \sum_{\substack{Ag^{(j)} \in \boldsymbol{G}^{(i)} \\ b \in B^j}} \pi_b^j K_{\Sigma_b^j}\left(\left\|x - \mu_b^j\right\|\right). \qquad (6.11)$$

After updating its KD function, of $Ag^{(i)}$ can perform a hill-climbing optimization procedure to identify clusters in its local data space.

To measure the clustering similarity [44] among the agents $Ag^{(i)} \in \boldsymbol{Ag}$ we use the following representation of a class labeling by a matrix C with components:

$$C_{i,j} = \begin{cases} 1 \text{ if } x_i \text{ and } x_j \text{ belong to the same cluster and } i \neq j, \\ 0 \text{ otherwise} \end{cases}$$

Let two labelings have matrix representations $C^{(1)}$ and $C^{(2)}$, respectively. We define a dot product that computes the number of pairs clustered together $\langle C^{(1)}, C^{(2)} \rangle = \sum_{i,j} C_{i,j}^{(1)} C_{i,j}^{(2)}$. The Jaccard's similarity measure can be expressed as

$$J(C^{(1)}, C^{(2)}) = \frac{\langle C^{(1)}, C^{(2)} \rangle}{\langle C^{(1)}, C^{(1)} \rangle + \langle C^{(2)}, C^{(2)} \rangle - \langle C^{(1)}, C^{(2)} \rangle} =$$

7.0 EXPERIMENTAL RESULTS

In this Section we demonstrate some numerical results, which illustrate quality of considered DDPM methods (decentralized regression and decentralized clustering).

For our experiments, we consider real-world data from a traffic network in the southern part of Hanover (Germany). The network contained three parallel and five perpendicular streets, which formed 15 intersections with a flow of approximately 5000 vehicles per hour. The network is shown in Figure 7.

Figure 7 Road network in the southern part of Hanover, Germany

Available data consists of a dependent variable Y (travelling time) and six factors $\mathbf{X}^{\langle 1 \rangle}$ - $\mathbf{X}^{\langle 6 \rangle}$. These factors are shown in Table 1.

Table 1. Available traffic data from Hanover, Germany

Variable	Description
Y	travelling time (min);
$\mathbf{X}^{\langle 1 \rangle}$	route length (km)
$\mathbf{X}^{\langle 2 \rangle}$	average speed in system (km/h)
$\mathbf{X}^{\langle 3 \rangle}$	average number of stops(units/min)
$\mathbf{X}^{\langle 4 \rangle}$	congestion level (vehicles/h)
$\mathbf{X}^{\langle 5 \rangle}$	number of the traffic lights in the route (units)
$\mathbf{X}^{\langle 6 \rangle}$	number of the left turns in the route (units)

7.1 Decentralised regression

First, we consider travelling time forecasting using regression models. We considered the linear and kernel-based regression models as well as combined their results using two additional estimates. The first estimate was the optimum, were we supposed an 'oracle' model helped to select the best forecast (with a low forecasting error) from every forecast. The oracle model represented the best forecast that could be achieved using the linear and kernel regressions.

The second 'average' estimate was the average of the kernel and linear estimates. There was a strong positive correlation between the linear and kernel estimates (about 0.8) but we demonstrated that the average estimate was often better than the kernel or linear estimates.

We compared the results by analysing the average forecasting errors, the relative forecasting errors and coefficients of determination R^2. These characteristics are well-known measures of the effectiveness in predicting the future outcomes using regression models and they can be used with parametric and non-parametric models.

We compared the average forecasting errors using different models (Figure 8). The kernel model was c. 5% better than the linear model. The average estimate was similar to the kernel estimate, but it was slightly better (2%). The oracle model is considerably better than the other estimates (c. 40% better than the kernel model).

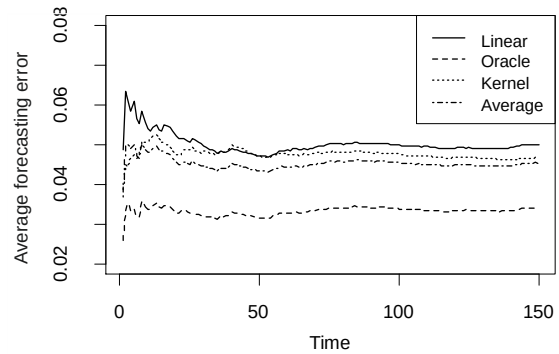


Figure 8. Average forecasting errors using the kernel, linear and combined approaches

Now, we show the system dynamics for one randomly selected agent (Figure 9). Large errors disappeared over time and the number of communication events also decreased.

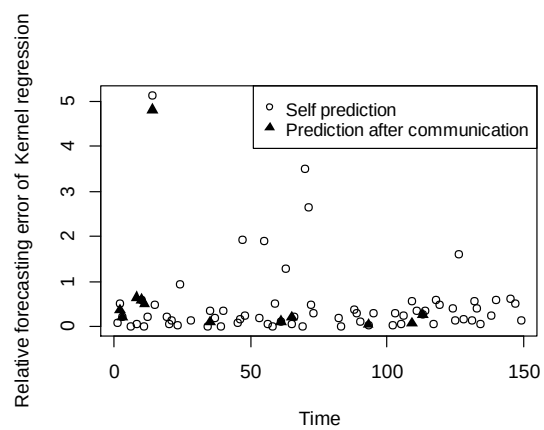


Figure 9. System dynamics of single agent using kernel model

Now we compare decentralized approach with other alternatives. Table 2 summarises the results of the average forecasting errors and goodness-of-fit criteria R^2 using the different forecasting models (linear, kernel, average, and oracle) with various architectures. We call above considered architecture decentralized coordinated. As alternatives we considered centralised architecture (with a central aggregation of all data) and decentralised uncoordinated architecture without information exchange between agents.

The linear regression model used all the data points for forecasting. This meant that the straight regression line was being adjusted continuously via coordination and new data points, so it could not be fitted well for all data points. The centralised architecture was worse because a single line could not make good forecasts for a big number of data points. The linear model within the uncoordinated architecture was worse

due to the convergence of the parameters of several agents to local optima instead of global optima.

The kernel-based regression model used only neighbouring points for forecasting. Coordination greatly improved the quality of forecasting because new neighbouring data points were provided. The centralised architecture made the best forecasts because there were many nearby points for most requested point. However, absence of experience (uncoordinated architecture) produced bad forecasts. Coordination sufficiently improved the R^2.

Analysis of the relative forecasting errors showed that the average estimator in coordinated and uncoordinated architectures for relatively small amounts of data produced relatively better results than kernel-based or linear estimators. The kernel model was more accurate on average, but it sometimes yielded highly inaccurate forecasts. The linear model was less accurate, but it did not produce such big outliers. The average method avoided big outliers of the kernel model and it provided more accurate forecasts.

The oracle-based estimator, which combined the kernel-based and linear estimators, provided a possible lower bound for the average forecasting error. This algorithm could improve forecasts by c. 25%. However, it is still unclear, how to choose between kernel-based and linear estimates.

Table 2. Average forecasting errors and goodness-of-fit criteria R^2 for the different forecasting models

Model	Average forecasting errors	R^2 (After cross-validation)
Linear		
Centralised	0.051	0.829
Uncoordinated	0.054	0.811
Coordinated	0.050	0.819
Kernel-based		
Centralised	0.045	0.913
Uncoordinated	0.053	0.814
Coordinated	0.047	0.859
Aggregated (average)		
Centralised	0.046	---
Uncoordinated	0.049	---
Coordinated	0.046	---
Aggregated (oracle)		
Centralised	0.034	---
Uncoordinated	0.037	---
Coordinated	0.034	---

7.2 Decentralised clustering

Second, we considered decentralized clustering of data listed in Table 1. The autonomous KD clustering and the decentralized cooperative clustering algorithm was used in our experiments.

We illustrate a data synchronization step. The requesting agent asks for help for point A, the helping agent clustered the point using its own data, detected the corresponding cluster, and approximated it with the mixture of three normal distributions (shown as ellipses for two dimensional case with centres in B, C, D at Fig. 10). Then the helping agent sent the corresponding parameters to the helping agent. The helping agent added the obtained parameters as data points to its data and made new clustering. This allowed to improve clustering similarity of these two agents from 0.011 to 0.037.

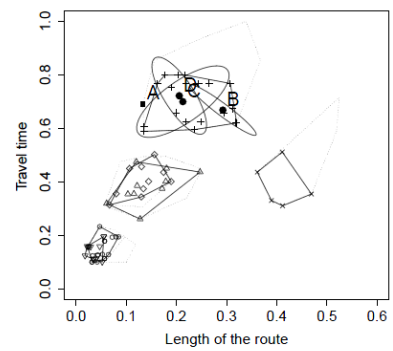


Figure 10 Approximation of a cluster containing A by three ellipsoids with centres in B, C and D

Now we consider a system dynamics for a different number of transmitted points. Clustering similarity (Fig. 11) increased faster for a bigger number of the estimated and transmitted components of normal distributions B^j for cluster approximations, but the number of communication events (Fig. 12) decreased faster.

Note, however, that one communication event was more expensive for a bigger number of transmitted points, but supplied more information.

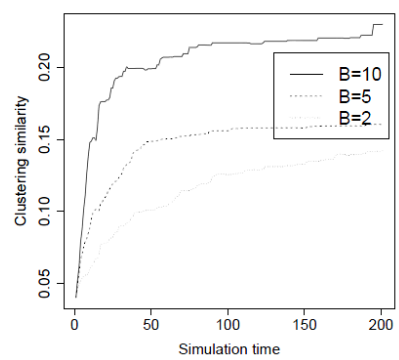


Figure 11 Similarity of agents' clusters over time depending on B components in a mixture of multidimensional normal distributions

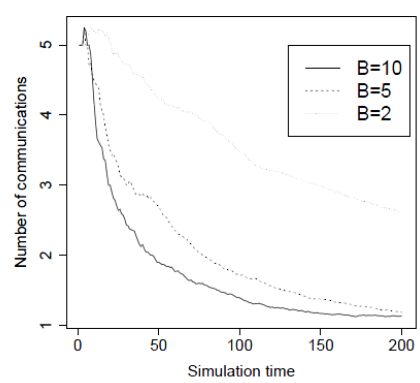


Figure 12 A number of communication events over time depending on B components in a mixture of multidimensional normal distributions

8.0 FUTURE WORK AND CONCLUSIONS

The main contribution of this study is a reference architecture for traffic cloud data mining and optimization of strategies (TCDMOS) and related data processing and network optimization methods. We envisage this as an important step towards making FI and cloud technologies usable for next-generation STMS. TCDMOS requirements were elicited from traffic scenarios, which reflect needs and impact of STMS for business and society, and the corresponding problems that should be solved for effective cloud system operation were illustrated. Future work will be devoted to elaborating the architecture, developing novel algorithms, and integrating and validating them in state-of-the-art cloud computing frameworks.

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