RIGA TECHNICAL UNIVERSITY

Jānis Pekša

MODULAR IMPLEMENTATION OF AUTONOMOUS DECISION MAKING ALGORITHMS IN ENTERPRISE RESOURCE PLANNING SYSTEMS

Summary of the Doctoral Thesis

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RIGA TECHNICAL UNIVERSITY
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To be granted the scientific degree of Doctor of Science (Ph. D.), the present Doctoral Thesis has been submitted for the defence at the open meeting of RTU Promotion Council on 30 November 2022 at 14.30 p. m. at the Faculty of Computer Science and Information Technology of Riga Technical University, 10 Embankment Zundas, Room 102.

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DECLARATION OF ACADEMIC INTEGRITY

I hereby declare that the Doctoral Thesis submitted for the review to Riga Technical University for the promotion to the scientific degree of Doctor of Science (Ph. D.) is my own. I confirm that this Doctoral Thesis has not been submitted to any other university for the promotion to a scientific degree.

Jānis Pekša…………………….…… (signature)
Date: ………………………

The Doctoral Thesis has been written in Latvian. It consists of an introduction, 6 chapters, conclusions, 72 figures, 22 tables, and 9 appendices. The total number of pages is 180, including appendices. The bibliography contains 298 titles.

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Topicality of the Research

Enterprise Resource Planning (ERP) systems are large, modular enterprise applications designed for most business processes. They are mainly intended for transaction processing. However, many modules have complex decision-making logic (Holsapple & Sena et al., 2019). Data processing logic is considered complex if it relies on analytical or management models to determine the direction of business processes and requires knowledge of other management models outside the ERP system. Forecasting is the process by which the future can be predicted on the basis of past data and through trend analysis (Januschowski & Gasthaus et al., 2020). Forecasting is one of the approaches that businesses need to process requests and make decisions in order to make more profit and continue their business processes successfully (Fiori & Foroni, 2020). ERP systems have limited prediction capabilities in the source code (Ruivo & Johansson et al., 2020). Businesses spend a lot of money adapting existing methods (Olson & Johansson et al., 2018). Some ERP systems do not have sufficient forecasting capabilities that substantiates the need to integrate forecasting algorithms into ERP systems.

The Goal of the Research

The goal of the Doctoral Thesis is to develop a framework that simplifies the integration of forecasting methods into ERP systems.

The Objectives of the Research

1. To analyse and evaluate the implementation of existing decision-making algorithms in ERP systems by performing literature analysis and case studies from various aspects.
2. To study the decision-making algorithms of the existing ERP system and to evaluate the possibilities of using data sources outside the ERP systems.
3. To design and develop a standard integration method that would provide a simplified integration process in ERP systems.
4. To formulate and implement an optimization model in a standard integration method.
5. To implement the forecasting algorithms in the designed framework.

6. To evaluate and develop a comparative analysis of autonomous forecasting, missing data source algorithms and framework forecasting.

The Hypotheses

Hypothesis 1. An autonomous data source processing algorithm improves forecasting accuracy.

Hypothesis 2. The developed integration method simplifies the integration process of forecasting methods in ERP systems.

Scientific Novelty

1. The method fills in the missing data with multiple layers of data to increase forecasting accuracy.
2. The method diversifies the integration of information provided by data sources for forecasting purposes to be implemented in ERP systems.
3. The autonomous framework for re-use of decision-making algorithms for forecasting, which allows obtaining the most up-to-date model, provides wider coverage and real-time forecasting.

The method is based on an approach that simplifies the integration of forecasting algorithms into ERP systems, which is complemented by controls and methods for evaluating specific decision-making algorithms. In order to make accurate forecasts, first, it is necessary to be aware of a decision-making algorithm to be used for a particular data source. Its successful selection requires a centralised evaluation method that can emphasise the choice of a decision-making algorithm. After successful selection, it is necessary to select a time series area, which mostly consists of missing observations for various reasons:

- To reduce or eliminate this situation, a method is needed that fills in the missing data to facilitate forecasting.
- When refining a result from a single data source, best practices indicate that multiple data sources are needed to strengthen the reliability of the results obtained. In this case, there is a need for a method that combines the information provided by different data sources in a common approach. The method increases accuracy from a variety of data sources. Integration of the respective method into ERP systems for

forecasting purposes by obtaining business internal data sources, as well as using external data sources, facilitates business process decisions.

- Reusable prototype that can be applied for standard use with other decision-making algorithms.

Research Methods

The scientific research methods used within the Doctoral Thesis (Fig. 1) are a systematic review of the literature and a method of engineering experimentation, which envisages the development of an analytical model, the development of an experimental design and statistical analysis of experimental results (Brinkkemper, 1996).

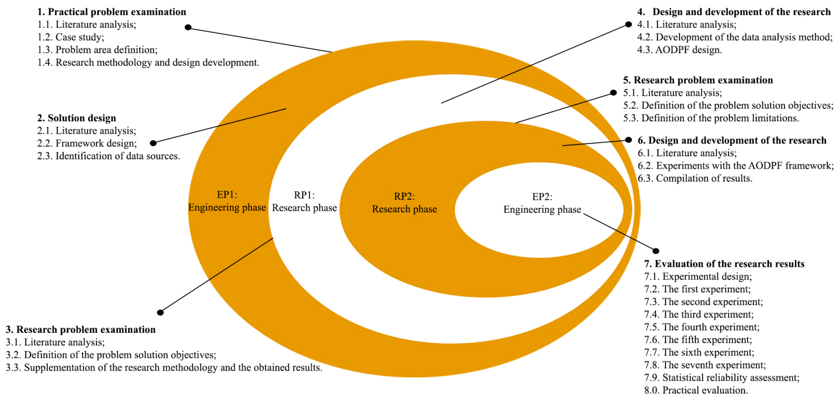


Fig. 1. Research methodology

Engineering phase EP1 consists of two parts. The first part is the practical problem examination, which includes literature analysis, case study, problem area definition, and research methodology and design development. The second part of EP1 is the solution design, which consists of literature analysis, framework design, and identification of data sources.

Research phase RP1 also consists of two parts. The first part includes the research problem examination, which consists of literature analysis, the definition of the problem solution objectives, and the supplementation of the research methodology and the obtained results. The second part of the research phase of RP1 is the design and development of the research, which consists of literature analysis, the development of the data analysis method, and the design of the Autonomous Open Data Prediction Framework (AODPF).

Research phase RP2 consists of two parts. The first part is the research problem examination, which consists of literature analysis, the definition of the problem solution objectives and the definition of the problem limitations. The second part of RP2 consists of the design and development of the research that includes literature analysis, experiments with the AODPF framework, and compilation of results.

In the last engineering phase – EP2, there is an evaluation of the research results, which consists of an experimental design with 7 experimental scenarios and a practical evaluation.

Within the framework of the Doctoral Thesis, modern research methods have been used: literature analysis, case study, data analysis methods, containerization, business process modelling, and expert evaluation methods.

Practical Implementation of the Research Results

1. Summary of shortcomings in the evaluation of ERP systems. By analysing the literature and conducting case studies, the summary identifies the most typical shortcomings in the integration of the ERP system. The summary can be used as a collection of knowledge that scientists and companies can use to improve the business processes of the existing ERP systems and to enhance future processes.
2. Improved capabilities of ERP system models, such as SAP ERP, MS Dynamics and Oracle ERP, which do not have full forecasting capabilities. There has been a decline in demand for a highly skilled workforce capable of programming in the ABAP programming language and others without the necessary forecasting methods. Forecasting methods need to be developed from scratch, and it is unprofitable. When making changes in the core of an ERP system, various challenges are observed, for example, the owner's system has a limited number of specialists who can perform a specific task. New fundamental changes in ERP systems need to be continuously improved in the long run, which is not always cost-effective. The proposed method will be freely available and integrated into the ERP system, regardless of the programming code and the availability of specialists. The method will also provide the basis for a repeatable solution that will be available to the general public.
3. New outsourcing opportunity for ERP system users and customers – the framework.

The Author's Publications in 2018–2022

1. Peksa, J., Grabis, J., Integration of the Autonomous Open Data Prediction Framework in ERP Systems. **In:** *Proceedings of the 24th International Conference on Enterprise Information Systems – Volume 1*. 2022. pp. 251–258. ISBN 978-989-758-569-2, ISSN 2184-4992 (contribution **90 %**, **Scopus**).
2. Pekša, J. Experimental Evaluation of Autonomous Open Data Prediction Framework (AODPF). **In:** *IEEE 9th Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE)*. Latvia, Riga, 25–26 November 2021. USA: IEEE, 2021, pp. 1–6. ISBN 978-1-6654-6712-4. ISSN 2689-7334. e-ISSN 2689-7342. Available: doi:10.1109/AIEEE54188.2021.9670032 (contribution **100 %, Scopus**).
3. Peksa, J., An Automated Algorithm Implementation to Fill Missing Points with Euclidean Approach. **In:** *Conference: 4th International Conference on Information and Computer Technologies (ICICT 2021)*. HI, USA, 2021 (contribution **100 %, Scopus**).
4. Peksa, J., Autonomous Data-Driven Integration into ERP Systems. **In:** *Design, Simulation, Manufacturing: The Innovation Exchange*. (pp. 223–232). Springer, Cham, 2021 (contribution **100 %, Scopus**).
5. Pekša, J. Prediction Framework Integration into ERP Systems. **In:** *2020 61th International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS 2020): Proceedings*. Latvia, Riga, 15–16 October 2020. Piscataway: IEEE, 2020 (contribution **100 %, Scopus**).
6. Pekša, J. Autonomous Data-Driven Integration Algorithm. **In:** *ICCBDC '20: Proceedings of the 2020 4th International Conference on Cloud and Big Data Computing*. Great Britain, Liverpool, 26–28 August 2020. New York: ACM, 2020, pp. 63–67. ISBN 978-1-4503-7538-2. Available: doi:10.1145/3416921.3416939 (contribution **100 %, Scopus**).
7. Pekša, J. Prediction Framework with Kalman Filter Algorithm. **In:** *Information*. 2020, Vol. 11, No. 11, Article number 358. ISSN 2078-2489. Available: doi:10.3390/info11070358 (contribution **100 %, Scopus**).
8. Pekša, J. Autonomous Open Data Prediction Framework. **In:** *The 7th IEEE Workshop on Advances in Information, Electronic and Electrical Engineering*

(AIEEE'2019). Latvia, Liepaja, 15–16 November 2019. Piscataway: IEEE, 2019 (contribution **100 %, Scopus**).

9. Grabis, J., Kampars, J., Pinka, K., Pekša, J. A Data Streams Processing Platform for Matching Information Demand and Data Supply. **In:** *Information Systems Engineering in Responsible Information Systems: CAiSE Forum 2019: Proceedings. Lecture Notes in Business Information Processing*. Vol. 350, Italy, Rome, 3–7 June 2019. Cham: Springer, 2019, pp. 111–119. ISBN 978-3-030-21296-4. e-ISBN 978-3-030-21297-1. Available: doi:10.1007/978-3-030-21290-2 (contribution **10 %, Scopus**).
10. Pekša, J. Adaptive Kalman Filter Forecasting for Road Maintainers. **In:** *Environment. Technology. Resources: Proceedings of the 12th International Scientific and Practical Conference*. Vol. 2, Latvia, Rezekne, 20–22 June 2019. Rezekne: Rezekne Academy of Technologies, 2019, pp. 109–113. ISSN 1691-5402. e-ISSN 2256-070X. Available: doi:10.17770/etr2019vol2.4134 (contribution **100 %, Scopus**).
11. Pekša, J. Forecasting Missing Data Using Different Methods for Road Maintainers. **In:** *Environment. Technology. Resources: Proceedings of the 12th International Scientific and Practical Conference*. Vol. 2, Latvia, Rezekne, 20–22 June 2019. Rezekne: Rezekne Academy of Technologies, 2019, pp. 104–108. ISSN 1691-5402. e-ISSN 2256-070X. Available: doi:10.17770/etr2019vol2.4120 (contribution **100 %, Scopus**).
12. Pekša, J. Decision-Making Algorithms for ERP Systems in Road Maintenance Work. **In:** *Information and Software Technologies: 25th International Conference (ICIST19): Proceedings*. Lithuania, Vilnius, 10–12 October 2019. Cham: Springer, 2019, pp. 44–55. ISBN 978-3-030-30274-0. Available: doi:10.1007/978-3-030-30275-7_5 (contribution **100 %, Scopus**).
13. Pekša, J., Rubulis, K. Operations Research Model Formulation for Road Maintenance Case. **In:** *Information Technology and Management Science*. 2019, Vol. 22, pp. 32–36. ISSN 2255-9086. e-ISSN 2255-9094. Available: doi:10.7250/itms-2019-0005 (contribution **100 %, EBSCO**).
14. Pekša, J. Forecasting using Contextual Data in Road Maintenance Work. **In:** *2018 IEEE 6th Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE 2018): Proceedings*. Lithuania, Vilnius, 8–10 November

2018. Piscataway: IEEE, 2018, pp. 1–6. ISBN 978-1-7281-2000-3. e-ISBN 978-1-7281-1999-1. Available: doi:10.1109/AIEEE.2018.8592085 (contribution **100 %, Scopus**).

15. Pekša, J. Extensible Portfolio of Forecasting Methods for ERP Systems: An Integration Approach. **In:** *Information Technology and Management Science*. 2018, Vol. 21, pp. 64–68. ISSN 2255-9086. e-ISSN 2255-9094. Available: doi:10.7250/itms-2018-0010 (contribution **100 %, EBSCO**).

16. Pekša, J., Grabis, J. Integration of Decision-Making Components in ERP Systems. **In:** *ICEIS 2018: Proceedings of the 20th International Conference on Enterprise Information Systems*. Vol. 1, Spain, Funchal, 21–24 March 2018. [S.l.]: SciTePress, 2018, pp. 183–189. ISBN 978-989-758-298-1. Available: doi:10.5220/0006779601830189 (contribution **50 %, Scopus**).

The author has 5 publications indexed in SCOPUS that are not related to the dissertation.

The Structure of the Doctoral Thesis

The Doctoral Thesis consists of six chapters. Chapter 1 provides a general description of the research, i.e., the problem to be solved is substantiated, the goal of the research is set, the objectives and hypotheses are formulated, as well as the research methodology, main results and the structure of the Doctoral Thesis are described. Chapter 2 defines the basic concepts used in the research and provides a literature review. Chapter 3 describes the design of the framework. Chapter 4 considers the forecasting solution. Chapter 5 deals with the experimental evaluation, which consists of seven experimental scenarios. Chapter 6 provides the practical evaluation of the framework using an expert evaluation method.

1. GENERAL DESCRIPTION OF THE RESEARCH

The ERP system implements several processes, and part of these processes is forecasting, which can be expressed as set *P*. As a result of process execution, the ERP system obtains transaction data set *D*. A set of historical data-based forecasting models *M* is used to obtain the required forecasts. Thus, the forecasting functionality implemented in ERP systems is characterised by the set *PERP* Equation (1.1):

$$PERP = < P, D, M > \tag{1.1}$$

The main disadvantage of the *PERP* forecasting approach is that it uses only the data and functionality available in the ERP system. An alternative to *PERP* is forecasting in a data warehouse, denoted *PDW*, where *P'* is the process in which forecasting is used. Data from the ERP system are denoted *D1* and data from external systems are denoted *D2*. Forecasting models are also used in the data warehouse, which are expressed as *M*. The obtained expression *PDW* is provided by Equation (1.2):

$$PDW = < P', D1, D2, M > \tag{1.2}$$

The limitation of *PDW* is that the process is statistical and is tied to a data warehouse schema. *PDW* extension is *IP* or an integrated forecasting approach. It combines *P1* and *P2* processes of the ERP system that take place in nature or actual events. For the *IP* access, data from the ERP system (*D1*) and data *D3* are available from various sensors or available outside the ERP system that measures the *P2* process. Unlike *D2*, *D3* is not tied to a data warehouse schema. IP is also an extended forecasting model *M'*, which has a wider range of models than the previous *M* forecasting model.

Data from the ERP system are denoted *D1,* and data from external systems are denoted *D2*. The forecasting models are also used in the data warehouse, which are expressed as *M*. The obtained expression *PDW* is provided in Equation (1.3):

$$IP = < P1, P2, D1, D3, M' > \tag{1.3}$$

The problem that is being solved is how to map *P2* to *P1* by attaching data. An example is road maintenance in the ERP system; *P1* is the road maintenance process, *D1* is information about roads in the ERP system that is limited to a specific road section length. *P2* is the actual road event (e.g., increased flow, accidents, ice freezes, etc.) and *D3* is sensor data whose main problem is that they are unevenly distributed (e.g., there is a sensor in one location and the other location lacks a sensor). In the ERP system, *D1* and *D2* are evenly distributed data, while *D3* are unevenly distributed data. The problem is in how the IP process could attract *D3* by mapping to obtain forecasts from the available *D*. The second example is customer demand forecasting, where the ERP system has a list of requests that require demand forecast PERP, while there is an *IP* process when customer information is variable and very different, each customer needs a forecast, then you can use the *IP* to map the data so that it is possible to make the appropriate forecast for each customer. Decision-making is defined as *L* in a specific case when M' reaches a certain threshold. The problem is solved in the branch of science "Electrical engineering, electronics, information and communication technologies" and in its sub-branch "System analysis, modelling and design".

The problems:

1. ERP systems have limited predictive power and need an IP approach.
2. ERP systems have limited resources to attract different data sources; there is a need for PWD lending through the IP process.
3. ERP systems have evenly distributed data, and the ability to capture unevenly distributed data requires an IP approach.
4. ERP systems have limited resources, and there is a need for large-scale resources for large-scale forecasting, as well as a need for an external solution.
5. There is a need to develop a model that would be able to perform data transformation, data preparation according to a unified model.
6. There is no common approach in ERP systems to provide IP capabilities, and there is a need for a framework.

The definitions of the basic concepts used in the author's research are the following:

- *Forecasting model* is used to forecast future data as a function of past data. They are useful when historical figures are available and when it is reasonable to assume that some of the data models are expected to continue in the future. The research defines it as *M*. Using algorithms as an approach, forecasting models are obtained by running algorithms over training data, and algorithms are used to obtain new forecasting models and new data, as well as their parameters, which are input forecasting models. Different data may have different forecasting models from the same data with different algorithms.

- *Decision-making model* contains at least one action axiom. The action is a rule in the form of IF-THEN. The action axiom checks IF-THEN before the condition is met on the basis of knowledge to make a decision. The decision model can also be a network of related decisions, information and knowledge, representing a reusable decision-making approach.
- *Framework* is a forecasting solution with a reusable framework prototype, consisting of a forecasting solution with several built-in forecasting methods, such as *AR, ARMA, ARIMA* and Kalman filter, the results of which can be integrated into ERP systems using a standard integration method.
- *Integration method* is a gradual implementation process from the available data to the receipt of results in ERP systems that can be used regardless of the diversity of data and the diversity of the ERP system. The technical solution is a web service that is able to provide integration between the web service and the use of ERP systems.
- *Forecasting solution* is a data processing method that allows assessing the availability and quality of data, for example, if the data are missing. The missing data method allows filling in the missing data so as to be able to improve forecasts. Fixed forecasting methods are used for specific data to obtain the best model for specific data points. Preprocessing is performed and existing forecasting methods are used in a forecasting model that is able to automatically determine how many data points to take to be able to determine the best forecasting model in a particular forecasting method in order to predict future trends. Preprocessing and identification of the best forecasting model allow obtaining a decision-making model that is defined by the decision maker with certain thresholds that must be met in a particular case.
- *Data processing method* – several data processing methods need to be used. Firstly, there is a need for data collection methods, i.e., data are collected, for example, from different data sources: freely available, company data, and freely available national data. Secondly, data preparation is used to determine whether the data are true and whether the data should be transformed into discrete time series; thirdly, the analysis of research data is carried out to determine the trend, stationarity and seasonality of data required for forecasting methods.

2. LITERATURE REVIEW

To determine the current level of knowledge and the area of research, a systematic review of the literature has been conducted. Bibliographic databases such as Scopus, Web of Science, etc., as well as tools for analysing bibliographic data have been used within the framework of the research (Donthu & Kumar et al., 2020).

Table 2.1

The Original Set of Keywords

Keywords
Enterprise resource planning (ERP) systems
Decision-making
Forecasting
Information system integration
Advanced planning systems

When selecting results from the Scopus database by keywords from Table 2.1, the total set consists of 1,080,440 documents (20 March 2021) (Pekša & Grabis, 2018). To make the search results more accurate and relevant, only scientific articles that are freely available have been selected. They were published in English for the period from 2017 to 2020. Considering that the scientific articles available over the past 5 years represent the most relevant result, 1,582 documents have been exported to the VOSviewer tool for an in-depth analysis. The in-depth analysis makes it possible to find application of forecasting methods in various URP systems (Ren & Chan, 2020). In VOSviewer (Fig. 2.1), the greatest attention is paid to two keywords: “decision-making” and “forecasting”, which are among the main active keywords. Creating a total of 13 clusters, of which the “decision-making” cluster accounts for 524 links with a total link effect of 18,123 and the “forecasting” cluster accounts for 474 links with a total link effect of 2,407.

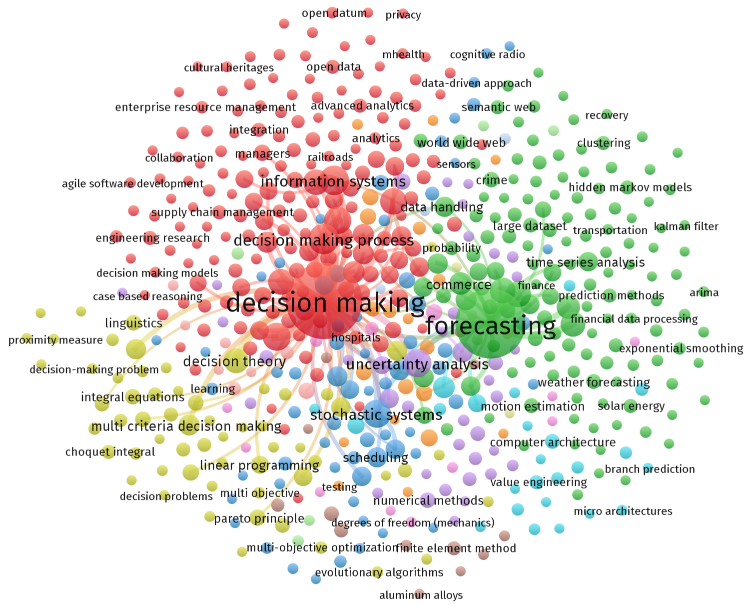


Fig. 2.1. Relation of the selected keywords

As a result of the literature review, the research area is highlighted (Fig. 2.2). It consists of three components: ERP systems, data sources, and the integration process between ERP systems and data sources. Point A describes studies of the main ERP forecasting methods that are available in ERP systems and can be used with existing data sources available in a centralised database. Point B is the internal integration of an ERP system where integration with other data sources is available. Point C is ERP system data that are limited to information in an existing centralised database and there is a need for external data sources for the purpose of forecasting. Point D – attraction of various data sources – is the area between ERP systems and external data sources that are the subject of the research.

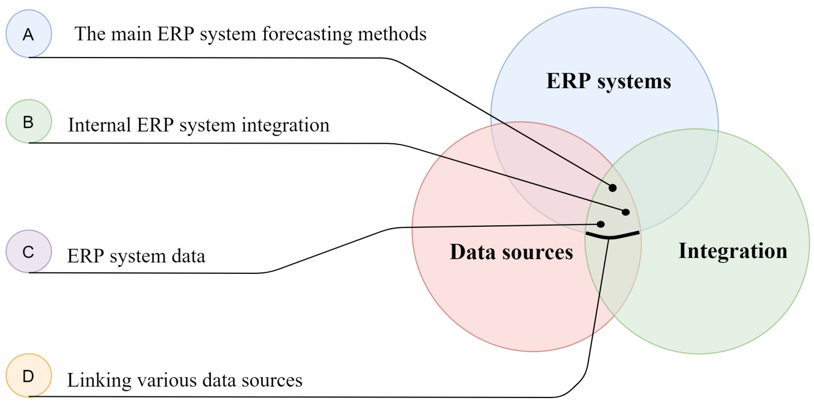


Fig. 2.2. The result set of literature review

From the literature review it can be concluded that the forecasting methods of the basic ERP system are limited and do not cover all forecasting methods. Internal ERP system integration and available resources are limited. The data in the ERP system are not sufficient to increase forecasting accuracy. To solve the problem mentioned above, it is necessary to use a number of forecasting methods and various data sources available outside the ERP system to improve forecasting accuracy.

3. FRAMEWORK DESIGN

A framework called Autonomous Open Data Prediction Framework (AODPF) has been developed for the integration of forecasting models into ERP systems (Pekša, 2019a). It supports the IP forecasting approach that is required to be able to perform forecasting with open data from a variety of sources. The AODPF provides automated algorithm selection and ensures the transfer of results to ERP systems.

Within the AODPF framework (Fig. 3.1), the forecasting and data processing functionality is separated from the ERP system, which implements the business process *P* that requires forecasting. The forecast is provided by an approximate real-time forecasting component. Real-time, historical data and autonomous best model selection are used for forecasting. Real-time data sources are actual process measurements and contextual data extracted from open data sources and business information systems. The first feedback also allows for the integration of current data from the ERP system. Data streaming tools are used for real-time processing. During the transformation, the data are reordered and the missing data are filled in (Pekša, 2019b; Pekša, 2021a).

One of the most important features of the AODPF is the choice of the best autonomous model. It uses a model base that provides information on different forecasting models. The model selection algorithm finds a suitable data set for forecasting and evaluates the suitability of models for these data sets. The model base can be supplemented with various models adapted to the problem area. Configuring the dataset allows accounting for structural changes in the data. The best model is used to predict and evaluate forecasting accuracy. The real-time approximate forecasting component defines the business rules in which the forecast affects the execution of business processes. Based on the forecast, a decision is made on the further direction of the business process, which is transmitted to the ERP system. The ERP system returns data on the efficiency of the processes, which allows for better decision-making. The second feedback ensures the application of new parameters *M'* from the ERP system (Pekša & Grabis, 2018; Pekša, 2018a).

The AODPF provides the forecasts necessary for the ERP system and also allows separating the functionality of performing business processes of the ERP system and forecasting from the point of view of calculations, which is an analytical task. The AODPF combines and processes data from different data sources and selects the most appropriate forecasting model for a specific situation. Its framework has several components: the source data component is a reference to C with D from D1, D2, and D3. Data streaming tool component ensures data availability and capabilities through the use of various tools. Data transformation component is utilised to make forecasts using the missing data point filling approach and data transformation to time series. Autonomous best model selection component finds and maintains the best model in the knowledge base. Proximity real-time forecasting component provides real-time forecasts using knowledge-based models (Pekša, 2021b).

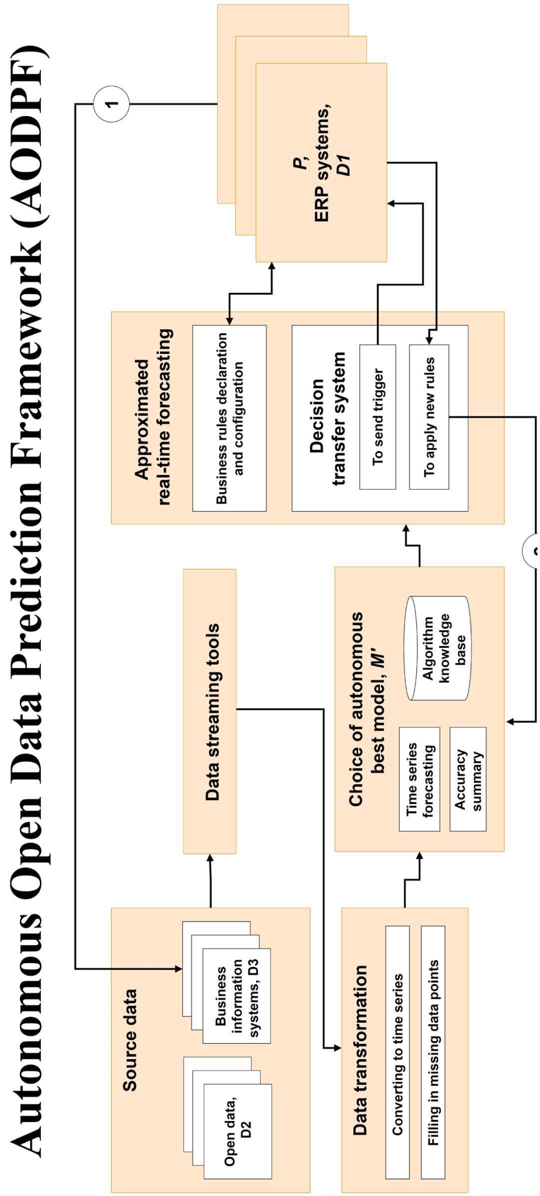


Fig. 3.1. The AODPF framework

4. FORECASTING SOLUTION

The work of the AODPF framework is based on data transformation and an algorithm for choosing the best model (Fig. 4.1). The extended forecasting model M', which is applied in the AODPF framework, uses transaction data D1 and external data D2 available in the ERP system and needs to be supplemented with D3. M' uses the best model selection components of the AODPF framework. D3 can increase the potential accuracy of predictions derived from a knowledge base that stores multiple M' as extended prediction models. It is advantageous to use a predefined extended prediction model and to use a known M' without repeating the algorithm components of the best model selection if the input parameters have not changed for unevenly distributed data D3 and D1, then data D2 are used, which have not changed. The ERP system implements several processes and part of these processes is forecasting P. In the ERP system, P obtains the transaction data set D. The set of forecasting models based on historical data necessary for the execution of process P is used to obtain M. The forecasting functionality implemented in ERP systems has been characterised by the set PERP. An alternative to PERP is forecasting in a data warehouse PDW, where P' is the process that uses forecasting. Data warehouse M also uses forecasting models. The PDW extension is an IP integrated forecasting approach. It combines the ERP system processes P1 and P2, and actual events. For the IP access, data from the ERP system D1 and data D3 are available from various sensors or available outside the ERP system that measures process P2. In the AODPF framework, data C are transferred to the regularization process, if necessary, data clustering is performed in C*, if not, then it is transferred to M'. The algorithmic knowledge base stores historical prediction results. The link between the ERP system and the AODPF framework is maintained, where IP1 and IP2 combine to form an integrated forecasting process expressed as an IP combined. IP1 is the integration of the road maintenance process, and IP2 is the actual events on the road integration. A link to the ERP system provides the transmission of parameters to the AODPF framework, as well as the transmission of a trigger with a certain result.

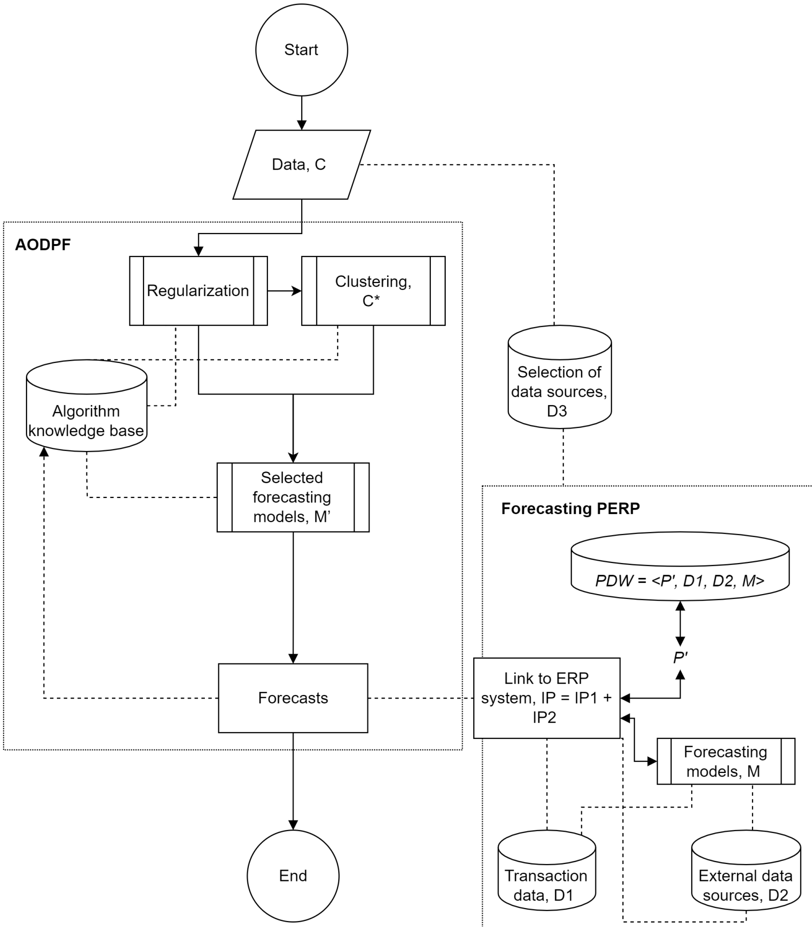


Fig. 4.1. Algorithm for AODPF framework operation

The integration of the algorithm into the AODPF framework is important for continuous forecasting. Without the appropriate addition of the algorithm to the AODPF framework, it is not possible to fill in the missing data. Using the standardized model content (Fig. 4.2), the algorithm is implemented in the AODPF framework.

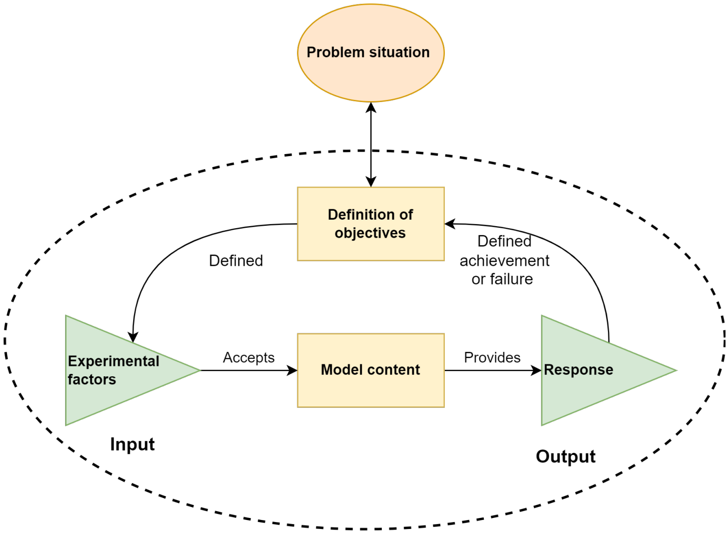


Fig. 4.2. Conceptual model of integration model (Robinson, 2008)

Forecasting is used in the decision-making model that generates decisions. The decision-making model is specific to a particular problem area. In the Doctoral Thesis, the model is formulated in the form of a linear programming model and is intended for making decisions on the maintenance of roads (Pekša & Rubulis, 2019). To determine the mathematical model, the problem of road maintenance is that it is necessary to know whether the condition of the road is satisfactory or dangerous in the winter months and at what point the road repairman should react. If the road surface is in a satisfactory condition at a certain stage, repair work is not required. If the condition of the road is unsatisfactory, it is necessary to carry out repair work. To forecast the condition of the road, data from roadside meteorological stations are used, the number of which increases every year, but still unevenly covers the territory of the country (Pekša, 2021c; Pekša, 2020b; Pekša, 2020c).

The AODPF framework provides road condition forecasts, which are used in a mathematical forecasting model to make decisions about the organisation of road maintenance data. In the decision-making model, there is a forecast generated by the framework, as well as the data about specialized trucks at the disposal of the road operator. The decision-making task is to determine which cars will be used to service certain sections of the road. The parameters and variables of the mathematical model have been determined in Table 4.1.

Table 4.1

Terminological Description of Parameters and Variables of the Road Maintenance Problem Optimization Model

Parameters and variables	Descriptive part
$t_1, t_2, \ldots, t_{n+1}$	observations (time series points)
F	a set of orders for all sections of the target road in a road maintenance problem
f	road segment order index and $f \in F$
ω_f^-	maintenance service order origin index f
ω_f^+	maintenance service order target index f
$send_f$	time of issue of the maintenance order at the time of its occurrence
$[arrive_f^-, arrive_f^+]$	the time schedule for the arrival of the maintenance service order f requested by the road operator, where $arrive_f^-$ is the lower limit and $arrive_f^+$ is the upper limit of the time window
R	road section of the road network of the Republic of Latvia
A	road network direction
T	service kit for network maintenance
i, j	road section parameters $i, j \in R$
(i, j)	direction from road section i to road section j $(i, j) \in A$
k	maintenance
q_{ijk}	maintenance service k q_{ijk} has the total capacity of a group of specialized vehicles that it can provide
N_{ijk}	maintenance costs per specialized truck unit in the direction of maintenance service k (i, j)

(Table 4.1 continued**)**

Parameters and variables	Descriptive part
N_{pen}	penalty costs per unit of specialized truck per hour
T_{ij}	the maintenance service is specified in direction *(i, j)*, and $T_{ij} \subseteq T$
x_{ij}^{f}	variable 0–1: if the specialist maintenance truck is on call in direction (i, j) $x_{ij}^{f} = 1$; or vice versa, $x_{ij}^{f} = 0$
y_{i}^{f}	non-negative variable: time of arrival of the specialized truck for maintenance order *f* on road section i.

The aim of the optimization model is to minimise the total costs of using specialized trucks in the road maintenance service. The cost of ordering the service can be calculated by Equation (4.1), where (*i* = 1, 2, …, *n*) and (*j* = 1, 2, …, *n*), and the cost of the late payment penalty by Equation (4.1).

$$minimize\ \sum_{f\in F}\sum_{(i,j)\in A}\sum_{k\in T_{ij}} N_{ijk} \times x_{ijk}^{f} +$$

$$+\sum_{f\in F} N_{pen} \times \begin{bmatrix} max\left\{arrive_f^{-} - y_{\omega_f^{+}}^{f}, 0\right\} + \\ max\left\{y_{\omega_f^{+}}^{f} - arrive_f^{+}, 0\right\} \end{bmatrix}. \tag{4.1}$$

The formulation of the constraints in Eq. (4.2) ensures that only one repair truck operates at a given destination:

$$\sum_{k\in T_{ij}} x_{ijk}^{f} \leq 1 \quad \forall f \in F \quad \forall (i,j) \in A\ . \tag{4.2}$$

Equation (4.3) guarantees that each special truck for a service order will leave its location exactly at the specified time.

$$y_{\omega_f^{-}}^{f} = send_f \quad \forall f \in F \tag{4.3}$$

Equations (4.4) and (4.5) restrict the ranges of values of both variables according to their definitions.

$$x_{ijk}^{f} \in \{0,1\} \quad \forall f \in F \quad \forall (i,j) \in A \quad \forall k \in T_{ij} \tag{4.4}$$

$$y_{i}^{f} \geq 0 \quad \forall f \in F \quad \forall i \in R \tag{4.5}$$

Equation (4.6) indicates that only available maintenance vehicles can be used.

$$\left\{ \sum_{f \in F} x_{ijk}^{f} \leq q_{ijk} \right\} \geq \alpha \quad \forall (i,j) \in A \quad \forall k \in T_{ij} \tag{4.6}$$

The introduction of AODPF provides a full cycle of forecasting and decision-making from the available data to obtaining results. ERP systems have an integration method that can be used regardless of the diversity of data and the diversity of the ERP system. The AODPF technical solution is a web service capable of receiving and transmitting data to the ERP system (Pekša, 2019b).

To demonstrate the forecasting solution (Pekša, 2018b; Pekša, 2019c; Pekša, 2019d; Pekša, 2020a), the data set of the SJSC "Latvian State Roads" is used in the period from 1 December 2016 to 1 March 2017. At LV01 meteorological station, which does not contain missing data, one of the most important observations in the data set is the dew point, which determines the formation of icing on the road (Fig. 4.3).

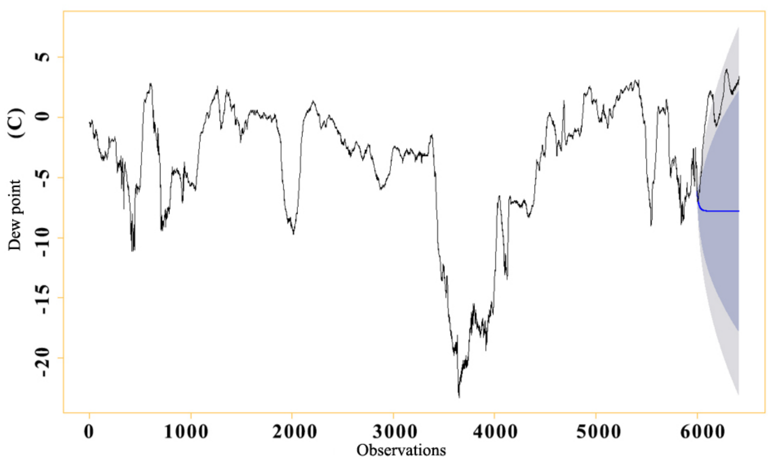


Fig. 4.3. Dew point LV01 forecast from 1 December 2016 to 1 March 2017

As a result of the choice of the best model, it has been determined that the most suitable forecasting model is ARIMA (4,1,5), the values of which and the prediction accuracy of the square root of the root mean square error (RMSE) are given in Table 4.2.

Table 4.2

ARIMA (4,1,5) Model Coefficients and Forecasting Accuracy

AR1	AR2	AR3	AR4	MA1	MA2	MA3	MA4	MA5	RMSE
0.53	–0.06	–0.26	0.66	–0.58	0.14	0.33	–0.71	0.08	0.205

To make forecasts, it is necessary to fill in the missing data. Figure 4.4 provides a map of the Republic of Latvia with all LV54 meteorological stations.

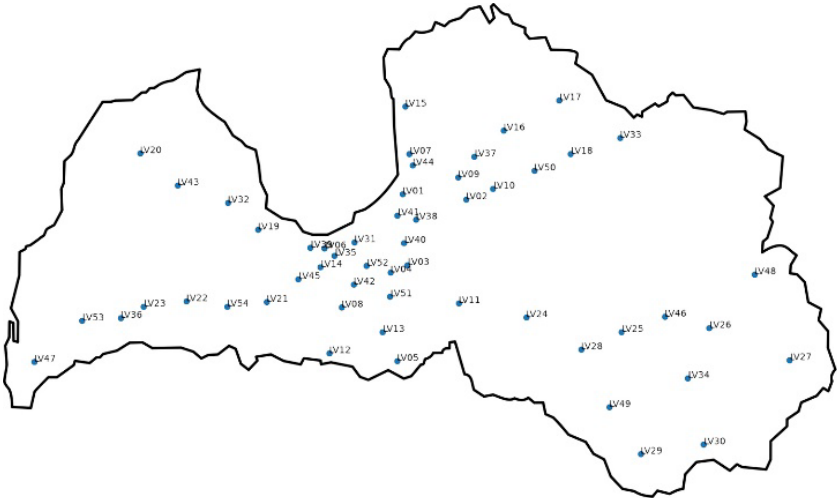


Fig. 4.4. Meteorological stations next to the road surface in the territory of the Republic of Latvia

In addition, the comparison of algorithms is used to fill in the missing data across the data set in each region and the results are shown in Table 4.3. A total of eight regions have been created, where missing data are filled in and forecasts are repeated and the total RMSE for each region is obtained. The expected value maximization algorithm and the *k*-means clustering show the best results, and in the re-evaluation, the *k*-means clustering demonstrates one of the best results, which is also used in the AODPF framework.

Table 4.3

Algorithm Results by Region

Algorithms	**RMSE for each region**							
	R1	R2	R3	R4	R5	R6	R7	R8
Moving average	0.02	0.36	0.38	0.36	0.54	0.83	0.62	0.48
Arithmetic mean	0.05	0.10	0.35	0.43	0.55	0.79	0.70	0.50
Bayesian average	0.10	0.27	0.37	0.39	0.53	0.73	0.65	0.47
k-means clustering	0.03	0.16	0.37	0.36	0.52	0.77	0.64	0.51
Expectation-maximization algorithm	0.02	0.09	0.31	0.30	0.49	0.69	0.58	0.44

The AODPF framework further uses *k*-means clustering.

5. EXPERIMENTAL EVALUATION

In an experimental evaluation, based on a systematic review of literature and best practices, the AODPF uses forecasting methods such as AR, ARMA, ARIMA and the Kalman filter. The base data layer is the ERP system path maintenance data. The additional data layer is the Latvian Environment, Geology and Meteorology Centre (LEGMC), which provides data from 25 Latvian urban meteorological stations. The aim of the experiment has been to evaluate the usefulness of the AODPF framework. The object of the experiment has been expressed in units of temperature °C and is available at each meteorological station in the territory of the Republic of Latvia for the period of 19 January 2020 – 19 January 2021. The AODPF framework is used to forecast the dew point. The AODPF framework uses the root mean square error to assess the accuracy of the forecasts provided. The experimental plan consists of seven experimental scenarios. In each experiment, the best forecasting method in the selected data set has been found automatically. The experimental plan with seven experimental scenarios and their factors is shown in Table 5.1. The experimental scenarios have been executed with Intel® Core™ i5 processor, while 20 computers have been used to run the experimental scenarios. Two hundred and forty experiments have been performed in all seven scenarios, with start times of 06:00, 09:00, 12:00, 18:00, and 21:00, and forecasting steps of 1, 5, and 10 for each scenario, for a total of 3,642.01 CPU hours. Thus, running such experimental scenarios on a single computer would take less than six months. The first experiment uses an external tool that provides results because it does not use the AODPF framework to compare the usefulness of AODPF with other external tools. The experimental plan is repeated twice to ensure accurate results.

Table 5.1

Experimental Plan with Seven Experimental Scenarios

Scenarios	**Experimental factors**				
	Without AODPF	With AODPF	Kalman filter	Filling in the missing data	LEGMC data set
No. 1	+	-	-	-	-
No. 2	-	+	-	-	-
No. 3	-	+	+	-	-

(Table 5.1 continued**)**

Scenarios	**Experimental factors**				
	Without AODPF	With AODPF	Kalman filter	Filling in the missing data	LEGMC data set
No. 4	-	+	-	+	-
No. 5	-	+	+	+	-
No. 6	-	+	-	+	+
No. 7	-	+	+	+	+

The results show that the AODPF framework reduces the root mean square error, which indicates its effectiveness by using different iterative methods with different data sets from different meteorological stations and an additional smoothing method, which is the Kalman filter. Scenarios Nos. 4–6 and No. 7 with missing data points have shown good results where the root mean square error decreases. The overall RMSE representation is provided in Figs. 5.1–5.3.

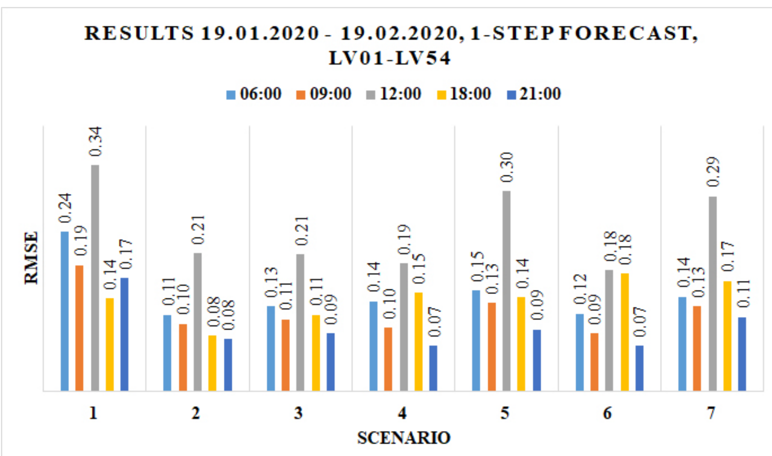


Fig. 5.1. RMSE representation of seven experimental scenarios for one-step forecast

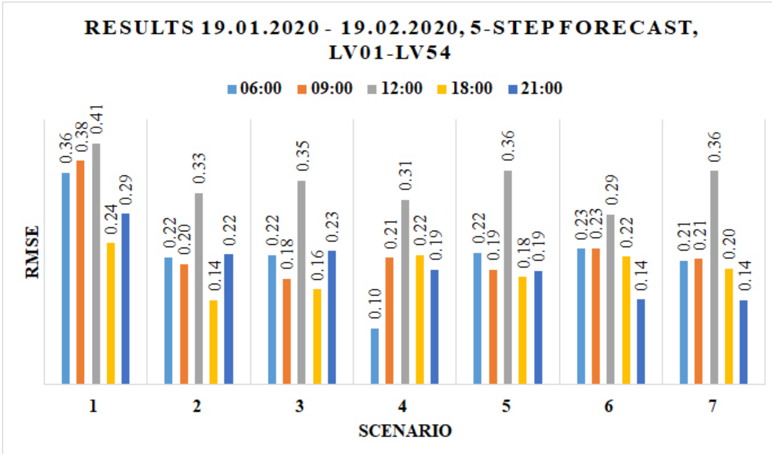


Fig. 5.2. RMSE representation of seven experimental scenarios for five-step forecast

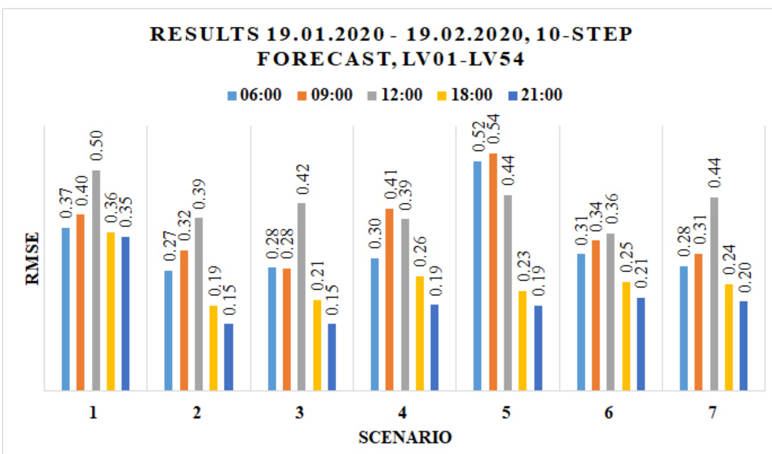


Fig. 5.3. RMSE representation of seven experimental scenarios for 10-step forecasts

The use of the data layer of the Latvian Centre for Environment, Geology and Meteorology improves forecasting accuracy by 1.03 % when using the Kalman filter. T-test and ANOVA are used to assess the statistical reliability of the experiments.

6. PRACTICAL EVALUATION

The accuracy of the framework has been evaluated from a practical point of view in an experiment performed in a natural environment. The usefulness of the framework is assessed in an expert survey.

Examples of a forecasting solution demonstrate that the AODPF framework can be used in the processing of real data. In one of the cases, which took place on 25 December 2020 in Riga from 4:30 p.m. to 4:45 p.m. on the South Bridge, there was an accident involving 18 cars caused by icing, with the dew point falling sharply. The relevant historical data were sent to the AODPF framework (Fig. 6.1).

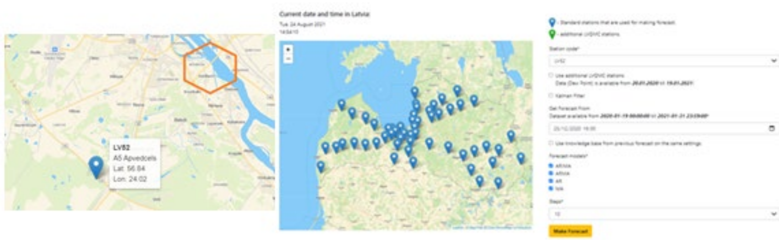
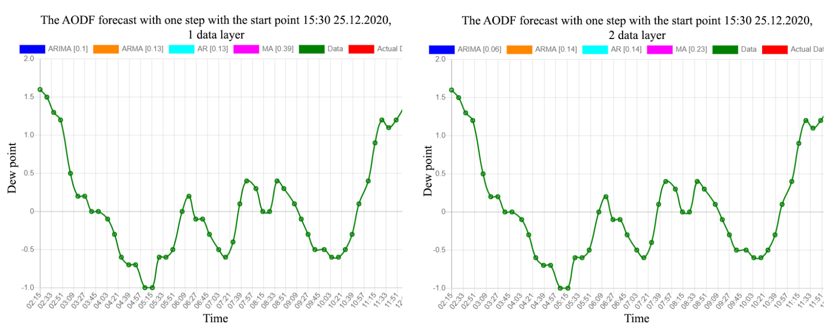


Fig. 6.1. The AODPF graphical user interface

The AODPF framework indicated the starting point from which to start forecasting, and it was LV47 at 12 p.m. on 25 December 2020 with one-step forecast. The results obtained with one data layer and with two data layers are compared in Fig. 6.2. It should be noted that the best results are demonstrated using two data layers.



a) b)

Fig. 6.2. Results: a) – on the first data layer; b) – additional second data layer

To assess the usefulness of the framework, the AODPF framework prototype approach was handed over to an expert group. 64 experts were contacted through well-known scientific portals. 21 experts were selected according to their focus and experience, and five experts participated in the practical evaluation. The task of the experts was to get acquainted with the author's publications and the developed AODPF framework, which was available to each expert using their own username and password.[1] When working with the AODPF and evaluating it in practice, the experts had to answer questions with ratings on a scale from 1 – strongly disagree to 5 – strongly agree. Cronbach's alpha value of the AODPF framework indicates that the practical evaluation of the AODPF framework is credible, as the value is higher than 0.85. Several comments indicate that the AODPF is difficult to use without knowledge of forecasting issues. However, the experts pointed out that, apart from the existing data sources, additional sources could be used as indicators of road traffic, possibly to improve accuracy. The experts also noted that the use of several forecasting methods was a complex process when placed in a single framework. The AODPF framework would make benefits if it were included in company ERP systems.

Overall Conclusions of the Research

The goal of the Doctoral Thesis was to develop a framework that allows reducing the integration of forecasting methods in ERP systems.

The most important conclusions obtained during the development of the Doctoral Theses are the following:

- Based on the existing solutions and forecasting methods, the implementation of decision-making algorithms for the interaction between the ERP system and forecasting has been analysed, and it has been proved that software as a service (SaaS) for data transformation, multi-layer use, forecasting and execution of repeated algorithms can be successfully applied.
- Using the SaaS approach, the AODPF framework has been developed and experimentally tested, which, unlike the existing frameworks, allows using different data sources, applying the missing data filling method, complex smoothing method, the knowledge base, several forecasting methods simultaneously, presenting

[1] https://github.com/JanisPeksa/Autonomous-Open-Data-Prediction-Framework

standard reusable solution ability, working autonomously and providing the required trigger to a specific context. It has been shown to be able to speed up the forecasting process and its processing runtime through a containerization approach and improve forecasting results.

- The results demonstrated the following:
  - According to the experimental evaluation carried out through seven experiments, a solution to the problem of missing data has been applied, which in the case of road maintenance amounts to 20.14 % of all data. It has been shown that using the paired t-test in seven experimental scenarios, a statistically significant p value is less than 0.05 and a two-factor unreplicated ANOVA result is considerable when the value of p is less than 0.05. It has been proven that a better result is achieved when the AODPF framework is used. It should be noted that in 20.14 % of cases it would not be possible to make forecasts at all. The use of an additional complex smoothing method such as the Kalman filter in the AODPF framework has demonstrated an increase in its efficiency by 0.33 %. Using an additional data layer in the AODPF framework, it has been proven that the use of the additional LEGMC data layer improves the forecast by 1.03 %, which indicates the usefulness and substantiates the use of other additional data layers. Using the AODPF integration model and the AODPF integration method, it has been demonstrated that the AODPF framework can implement ERP systems and delegate autonomous work tasks using a trigger.
  - according to the practical evaluation, the AODPF can be used as a SaaS and reused through a containerization solution. It has been shown that the execution time is exponentially reduced compared to the general approach. With simultaneous use of the programming development environment, 20 computers have been used to execute seven experimental scenarios, for a total of 3,642.01 CPU-hours. Using one computer in seven experimental scenarios would take up to six months to complete, or about 182 days.
  - out of 64 experts contacted, 21 experts have complied with the requirements and finally the practical evaluation has been carried out by the group of five experts. The expert group has unanimously stressed that the AODPF framework is practical and that its use facilitates the integration of results into the ERP system, and the value of Cronbach’s alpha demonstrates that experts have been

unanimous in their answers to the questions. The practical evaluation of the AODPF framework is credible, since the value is higher than 0.85, and the results are considered significant by the value of Cronbach's alpha. The experts have successfully used a mathematical optimization model for the case of road maintenance and obtained results through the API for the implementation of the ERP system from previously prepared autonomous works.

The AODPF framework has the following advantages:

1) the ability to fill in the missing data using data points of the two data layers;
2) the ability to use several forecasting methods simultaneously;
3) the ability to use complex smoothing techniques such as the Kalman filter;
4) the ability to work autonomously and provide the required trigger for a specific context, for example, whether a dew point reaches a certain threshold;
5) the ability to serve as a standard SaaS solution;
6) the ability to apply a containerization solution that can work and obtain results at the same time.

The hypotheses of the Doctoral Thesis:

1. *An autonomous data source processing algorithm improves forecasting accuracy.*
   Hypothesis 1 has been proven by using various data sources to improve forecasting accuracy, which has been confirmed by the performed experiments.
2. *The developed integration method simplifies the integration process of forecasting methods in ERP systems.*
   Hypothesis 2 has been proven by performing an experimental integration in the SAP ERP system, obtaining an independent connection to the ERP system. The developed integration method has been applied in practice.

The results of the Doctoral Thesis create an opportunity for further research:

- reusable results can be implemented in ERP systems;
- the AODPF framework allows using different data sources by linking several layers; currently there are only two data layers;
- implementation of the AODPF framework improves the efficiency of maintenance processes for a new type of smart winter road maintenance IS and ERP system integration solution.

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