Designing a Decision Support System for Predicting Innovation Activity

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Abstract: Decision support systems for predicting innovation activity at the macro level are not yet widely used, and the authors have not been able to find direct analogues of such a system. The relevance of creating the system is due to the need to take into account heterogeneous structured and unstructured information, including in natural language, when predicting innovation activity. The article describes the process of designing a decision support system for predicting innovation activity, based on the system for integrating macroeconomic and statistical data (described by the authors in previous articles) by adding a module of decision-making methods. The UML diagram of use cases and the UML diagram of the components of this module, the general architecture of the prototype of the decision support system, are presented. It also describes an algorithm for predicting innovation activity and its impact on the potential for economic growth using DSS.

1 INTRODUCTION

The progressive development of the country's economy and its level of competitiveness are inextricably linked to innovation activity. However, the concept under study is extremely complex and for its comprehensive assessment, it is necessary to evaluate a variety of indicators, both quantitative and qualitative. Innovation, investment, efficiency of knowledge management, problems of transferring knowledge from the fundamental to the practical sphere, influence of intellectual capital, susceptibility to innovations, as well as other factors need to be taken into account in order to assess and predict innovation activity.

Until now, the problem of automating the process of collecting and processing heterogeneous information in order to forecast innovation activity at the macro level has only been partially solved.

The previous stage of the study described a system for collecting macroeconomic and statistical data based on the ontology of innovation activity and economic growth potential (Korableva et al., 2018, 2019). Forecasting innovation activity and its impact on the potential of economic growth is a labor-intensive process that requires a lot of time and effort to prepare parameters for models, as well as to perform calculations. Creating a decision support system that provides models for predicting innovation activity at the macro level and its impact on economic growth potential by analyzing data from various types of sources (PDF, HTML, XLS, web services) would significantly increase the accuracy of forecasts of innovation activity, and, as a result, the effectiveness of decision-making in the field of managing a country's innovation development.

2 LITERATURE REVIEW

The most complete analysis of the DSS is given in the article (Wagner, 2017), affecting 311 systems. Let us consider the most important comparative characteristics.

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* The most popular areas of application of expert systems are accounting and financial services, manufacturing and medicine.
* The most popular way to acquire knowledge is to interview an expert in the subject area, including using questionnaires. Dependency diagrams, knowledge maps, cognitive maps, and decision trees are also used. The recent growth of popularity of automated knowledge acquisition methods may be related to increased interest in neural networks and ontologies. In addition, the multi-criteria group decision-making (MCGDM) method (Xue et al., 2020) is noteworthy.
* Rules are widely usable way to represent knowledge, while frames and cognitive maps are less popular.

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The literature covers the process of developing a DSS (Kossiakoff et al., 2011), describes in detail the process of elaborating a rules-based DSS. In (Dokas and Alapetite, 2006), modifications are described for developing DSS as a web application in order to increase the availability of the system via the Internet.

In General, it can be concluded that the scientific community is interested in DSS and actively developing methods for their building, including using neural networks and big data processing.

DSS are the most common in areas that have a fairly limited set of input parameters (compared to the model at the macro level). For example, the model for predicting the behavior of future customers provides key information for effectively directing resources to sales and marketing departments, planning inventory in the warehouse and at points of sale, and for making strategic decisions in the production process (Martínez et al., 2020). A model for predictive group maintenance for multi-system multicomponent networks (MSMCN) is also interesting (Liang and Parlikad, 2020). The key innovation in the model is that the developed approach combines analytical and numerical methods to optimize the service policy of predictive groups.

The article (Wu and Wu, 2020) presents a decision support approach for the network structured stochastic multi-purpose index problem. The authors also suggest an optimization - based approach to generating scenarios to protect against the risk of evaluating parameters for SMILP (Stochastic Mixed Integer Linear Program).

Building a decision support system at the macro level involves a lot of difficulties, such as the need to take into account a huge number of parameters, both qualitative and quantitative. A complete analogue of the developed system was not found. However, platforms that support the construction of macroeconomic models and forecasting are similar to the function being developed, such as Dynare, which is a software platform for processing a wide class of economic models, in particular dynamic stochastic general equilibrium (DSGE) and overlapping generations (OLG) models. Dynare internally uses a complex panel of applied mathematics and computer technologies: multidimensional nonlinear solution and optimization, matrix factorizations, local functional approximation, Kalman filters and smoothers, MCMC methods for Bayesian estimation, graph algorithms, optimal control, etc. (https://www.dynare.org/about/).

Also it is worth noting BI platform of a company Prognoz http://www.prognoz.ru/platform.This is an IT solution for creating applications that combines modern technologies of data storage, visualization, operational data analysis (OLAP), reporting, modeling and forecasting of various economic processes.

The approaches include vide range of analytical tools and gives opportunity to make forecasts. However, the set of tools used differs significantly from the one designed for this study and does not provide enough tools to evaluate qualitative non-formalized parameters.

3 RESULTS AND DISCUSSION

3.1 The Architecture of the Prototype of Decision Support System based on Ontology

Decision-making process (Kossiakoff et al., 2011) in the general case has 5 stages:

1. Planning the decision-making process, which defines:

a. Goals and objectives
b. Type of solution
c. Solution context
d. Stakeholders
e. Legacy solutions
f. Additional data

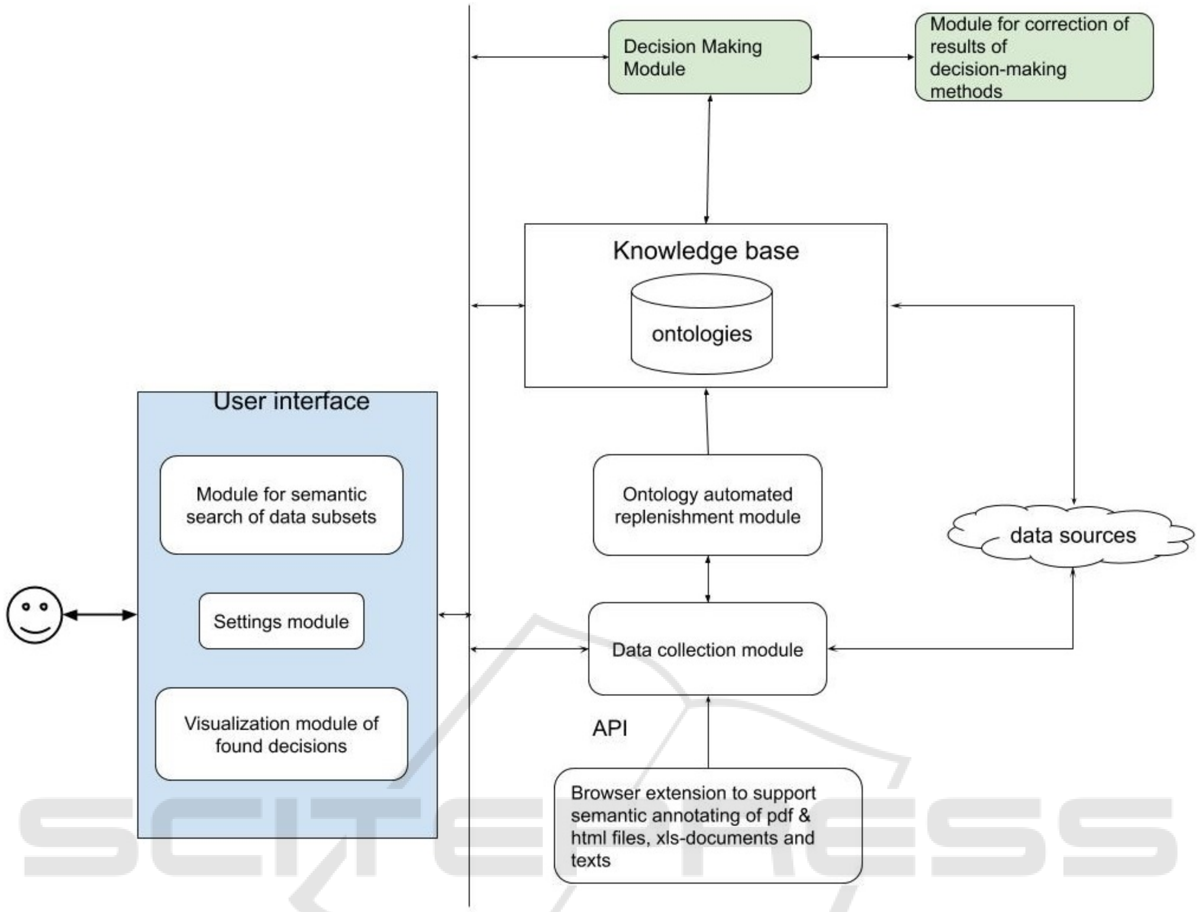

Figure 1: The General architecture of the DSS.

2. Data collection
3. Organization and processing of information
4. Taking decision
5. Implementation of decisions

In accordance with the logic of the study, point 1 was defined when determine the whole framework of the study (Korableva et al., 2018). Then the tasks of collecting macroeconomic and statistical data were solved on the basis of an ontological approach and building an ontology of innovative development and its impact on the potential for economic growth (automatic data aggregation system - ADAS).

At this stage, a decision support system (DSS) is being built on the basis of the ADAS, which would automate point 4, namely, provide models for predicting innovation activity and its impact on the potential for economic growth. At the current stage, a decision support system (DSS) is being built on the basis of ADAS, which would allow using automated approaches for decision-making within the process of forecasting innovation activity taking into account multi-factor influence.

It is supposed that using this type of system will increase the productivity of the decision-making process and improve the quality of the decisions themselves. The General architecture of the DSS is shown in Fig. 1

To consider a variant of the approach to automating forecasting, this paper describes the process of building a prototype of a decision support system based on the ontology of innovation activity and economic potential growth.

Since the DSS is designed as an extension of the ADAS, it is a client-server web application that the user interacts with through a web interface. The web application contains a module for collecting data from various types of sources (PDF, HTML, XLS, web services). Using this module, the web application receives potential RDF triples, which are first processed in the automated ontology replenishment module and stored in the knowledge base (KB). The KB is built on the ontology of innovation activity and economic potential. It also requests data to be displayed in the web interface by the semantic search system for subsets of data.

There are several types of classifications of forecasting methods. According to one of them, all forecasting methods can be divided into heuristic methods, which are based on the predominance of intuition, i.e. subjective principles, and economic and mathematical methods, which are dominated by objective principles (Sonina, 2014). To get a completer and more objective picture when building an empirical model for predicting innovation activity, we will consider methods from both groups. The vector autoregressive model and dynamic stochastic model of general equilibrium are chosen as an example of economic and mathematical approaches, while the technological foresight method represents heuristic methods.

Thus, several competing methods are used in the decision-making module:

* Vector autoregressive model (VAR)
* Dynamic stochastic general equilibrium model (DSGE)
• Neural network.

The module works as follows. The user of the DSS submits the necessary parameters for input by selecting them from the KB:

- For a neural network, the user selects a set of economic indicators for the past years, based on which it will be trained.
- For the vector autoregressive model, the user chooses indicators for forecasting the innovation activity of the economy as variables for building the VAR model and the period on which the forecast will be made.
- For DSGE, a list of parameters are selected. Some of them are set as constants, taking into account adaptation for the Russian economy.

This is followed by a prediction process, and results that can be installed by the user in the decision method adjustment module (for example, by changing the values of input parameters or adding them). The results obtained are used by experts in determining forecast data, and can also be introduced in the foresight system.

Despite the advantages of the DSGE model, there is a criticism of it, which highlights the following shortcomings (Andrianov et al., 2014):

* Using the concept of rational expectations, which assumes that economic agents make the most effective use of all available information and all available experience when making decisions;
* Using the representative agent principle, which reduces complex economic systems to separate elements, and as a result neglects holistic basis of a system;
* Applying filters depending on the selected method, smoothing parameters, initial and final filtering periods, and so on.
* Time-consuming procedure for deriving and parameterizing equations.

Therefore, in the course of the study, it seems appropriate to search for an analogue for this method, which most fully meets the tasks set.

3.2 UML Diagram of Options for using the Decision Methods Module

The UML diagram of the options for using the decision-making methods module is shown in Fig.2. Firstly, it is necessary to select the type of forecast model.

Also, economic indicators and forecast period are chosen. The indicators are submitted to the model as input data. In the DSS, these indicators are stored in the previously created ontology of macroeconomic and statistical data.

Next, preliminary steps before forecasting are performed. For DSGE models it is the calibration of input parameters, for the VAR model – definition of the maximum length of the lag, for the Neural network - training on selected economic indicators during the particular time period.

After that, the user receives the result of the selected forecasting models, which can be viewed in tabular and graphical form, filtered by different criteria. The results obtained by different methods can be compared with each other.

The models are built iteratively: each run can be followed by a process of adjusting the results, which changes the input parameters, and for the neural network – training on the adjusted data.

Thus, the decision-making module works as a "black box" for the end user: the user selects economic indicators to submit for input (the indicators themselves and their values for N years are stored in the ontology), and at the output receives the result of forecasting indicators.

3.3 UML-diagram of the Class of the Decision Methods Module

UML-diagram of the class of the decision methods module is shown in Fig. 3. Let us look at it

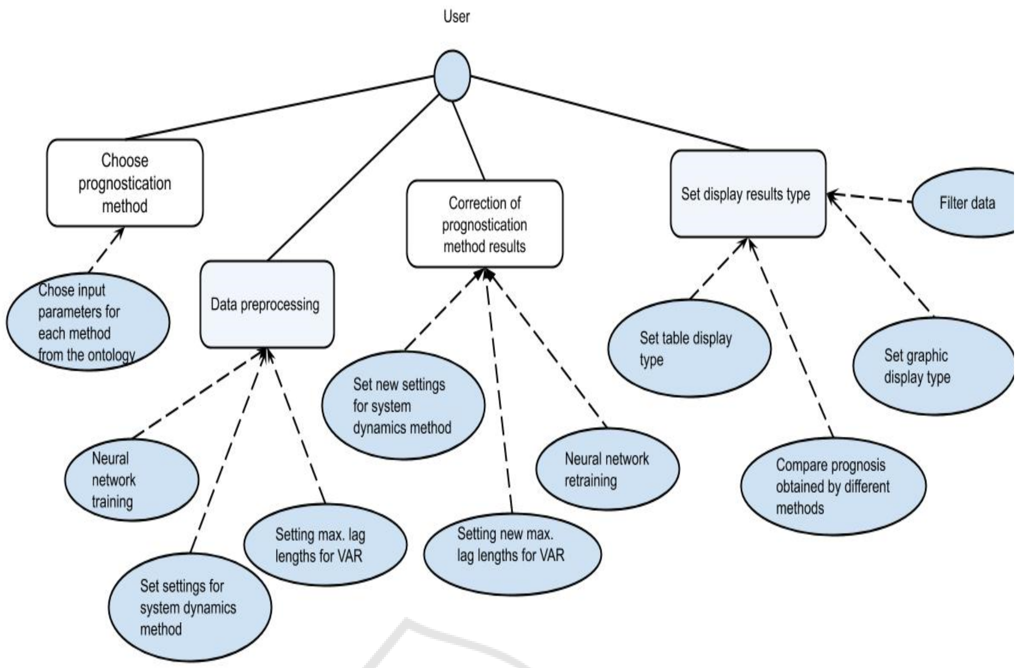

Figure 2: The UML diagram of the options for using the decision-making methods module.

in more detail. The main class for the decision module is Solutions. The class defines functions for getting all the getMethods () methods defined in the DSS, a function for selecting user-defined prediction methods for a specific case, setUserMethods (), and a function for starting the executePrognosis () prediction. The app interface get accesses to these features through the app API.

The Solutions class also stores a set of prediction methods described using the method classes in Fig. 3. This is DSGE, VAR, NeuroNetwork. Prediction methods implement the Method interface. Each method class contains a setMethodParams function to install input parameters for the method and an executeMethod () that performs method prediction (used in the executePrognosis).

The input parameters for each method are described by the DSGESettings, VARSettings, and NeuroNetworkSettings classes, which are inherited from the Settings interface. They contain collections of input parameters with values for each prediction method.

The prediction results for each method are also described by separate classes (DSGEResult, VARResult, and NeuroNetworkResult) and implement the Result interface. They contain collections of predicted parameters with values for each method.

The classes of the prediction result correction implement the ResultCorrection interface and contain functions for correcting the prediction results of a particular method by changing input parameters (setMethodParams).

The relationships between the prediction method and its settings, results, and correction class are shown only for the DSGE class for clarity as sample.

3.4 Algorithm for Predicting Innovation Activity and Its Impact on the Potential for Economic Growth using the DSS

Let's take a closer look at the steps that need to be taken when predicting innovation activity using the DSS. Steps 1-3 were described in more detail in the paper (Korableva et al., 2019).

1. Setting up the DSS by the operator. For the step, it is necessary to specify:

* Initial data sources of selected types (PDF and XLS documents, HTML pages, web services, and ontologies);

• System parameters for collection: the frequency of automatic collection, the need for automatic source search, and so on;

* Queries to find new data sources.

2. The data collection system collects data according to the algorithm depending on the types of sources and leads to the structure of the ontology.

3. The automated ontology replenishment system brings data to the ontology structure and saves it to

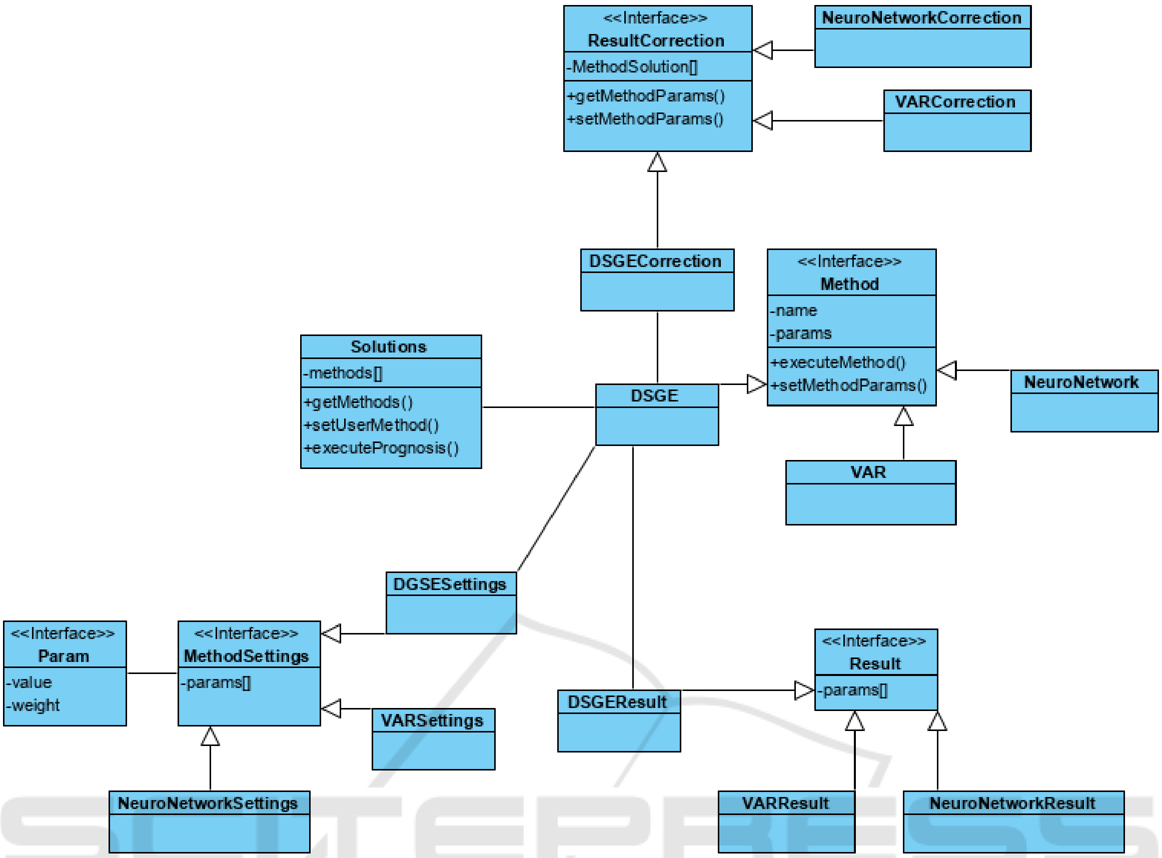

Figure 3: UML-diagram of the class of the decision methods module.

the knowledge base.

Steps 1-3 are realized iteratively for updating data and adding new sources.

4. An operator selects economic indicators (from those presented in the ontology) and the forecast period, and the information is passed as input parameters to the forecasting systems used in the DSS (DGSE model, VAR model, neural networks).

5. The operator initiates forecasting of innovation activity using the selected methods. The output provides results that characterize the forecast of macroeconomic activity (depending on the settings in the previous step and methods).

6. Experts make adjustments to the results obtained. In this case, the input parameters can be changed in order to check the response of the model, as well as to cut off the boundary values of the predicted indicators by a specific model. For a neural network, repeated training can occur on corrected input data.

Steps 5-6 are also undertaken iteratively until prediction models that satisfy the experts are got.

7. Data is transmitted to all interested parties for use in the technological foresight and creation of the most probable forecasting scenarios.

The developed system has been tested. The algorithm for predicting innovation activity and its impact on the potential for economic growth using the DSS was used by experts to forecast macroeconomic indicators for 2017-2019. During testing, insufficient accuracy was revealed due to deviations in the DSGE model. That is why further research is needed on how to more correctly simulate expectations in DSGE models or replace this model in the DSS.

4 CONCLUSION

This paper describes the process of designing a decision support system for predicting innovation activity, based on the system for integrating macroeconomic and statistical data (described by the authors earlier) by adding a module of decision-making methods. The UML diagram of use cases, the

UML diagram of the components of this module, and the General architecture of the prototype of the decision support system are presented. It also describes an algorithm for predicting innovation activity and its impact on the potential for economic growth using the DSS.

The presented DSS for forecasting of innovative activity allows to develop a knowledge base to build models to predict the target macroeconomic indicators (in particular indicators of the growth potential of the Russian Federation and innovative activity). It also gives opportunity to automate the process of building forecasting models for the target macroeconomic indicators, improving the quality of the results of the technological foresight with experts, and make the assessment more objective and reduce the time of forecasting.

The algorithm for predicting innovation activity and its impact on the potential for economic growth using the DSS has been subject to validation in the field of forecasting of the macroeconomic indicators for 2017-2019. In the future, it is planned to improve the models already used, as well as finalize the prototype of the DSS as the release version.

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