УДК 681.3, 004.6

Литвиненко Т.І., студентка,
Панченко Т.В., к.ф.-м.н., доц.,
Редько В.Д., студентка

Прогнозування продажів методами інтелектуального аналізу даних

Київський національний університет імені Тараса Шевченка, Україна, 01601, місто Київ, вул. Володимирська, 64/13
e-mail: tp@infosoft.ua

T.I. Lytvynenko, student,
T.V. Panchenko, PhD, assoc.prof.,
V.D. Redko, student

Sales Forecasting using Data Mining Methods

Taras Shevchenko National University of Kyiv, 64/13, Volodymyrska Street, City of Kyiv, Ukraine, 01601
e-mail: tp@infosoft.ua

Розглядається задача прогнозування продажів продукції за відомою історією продажів та без урахування додаткових факторів. Ця задача часто зустрічається на практиці, коли немає можливості використати факторний аналіз, і ми маємо покладатись лише на історичні дані. У даній роботі подано порівняльний аналіз трьох основних алгоритмів для задачі прогнозування. Дослідження включає традиційні статистичні методи та перспективні структурні алгоритми прогнозування, а саме: ARIMA (на базі рішення Microsoft SQL Server алгоритму часових рядів), еволюційного (або генетичного) алгоритму та побудови дерев рішень. Ми не будемо досліджувати комбінації методів, застосовуваних послідовно або паралельно, у цій роботі, хоча це питання також варто уваги. Основна увага в прогнозуванні зазвичай приділяється деталям реалізації. У даній роботі сконцентровано увагу на порівняльному аналізі переваг та недоліків кожного із зазначених алгоритмів. Отримане апріорне порівняння слід співставити з результатами застосування цих методів до реальних даних, аби перевірити кореляцію апостеріорних результатів, що буде зроблено у наступних роботах.

Ключові слова: прогнозування, ARIMA, ARTXP, еволюційний алгоритм, генетичний алгоритм, дерево рішень.

Forecasting of product sales by known sales history and without other factors influence task is the subject of this work. This represents real-life practical task when we cannot use factor analysis and must rely on historical data solely. This study presents a description and comparison of three basic algorithms of forecasting. Our research covers both traditional statistical and perspective structural predictive methods, including ARIMA (based on Microsoft SQL Server Time Series Model Query package), evolutionary algorithm (or genetic) and constructing decision forests. We will not analyze method combinations, sequentially applied nor parallel, in this review though it worth attention. Much of previous attention on forecasting focuses on its implementations. This study is concentrated on the comparative analysis of advantages and disadvantages of algorithms mentioned above. A-priory comparative results obtained here should be matched with results of these methods application to real-life data in order to correlate them and this will be done in the next papers.

Key Words: forecasting, ARIMA, ARTXP, evolutionary algorithm, genetic algorithm, decision tree.

Статтю представив д.ф.-м.н., проф. Буй Д.Б.

Introduction

The necessity of forecasting presupposes a paramount significance of the problems of prognosis. Forecasting of product sales by known sales history and without other factors influence task is the subject of this work. This represents real-life practical task when we cannot use factor analysis and must rely on historical data solely. Software solutions are built in order to cope with an enormous amount of data. In [1] it is observed that in general all predictive techniques may be divided into two principal groups: statistical and structural methods correspondingly. The first group includes predictive models, which leverages statistics to predict outcomes [2] – ultimate model is represented by analytical formula. The second group consists of step-by-step methods, where terminate algorithm looks like a definite set of stages. In our research statistical approaches are represented by ARIMA (implemented in Microsoft Time Series). Microsoft SQL Server [3] provides regression algorithms that are optimized for the forecasting of continuous values. Classical structural approaches are represented by decision trees, combined in random forests. According to [4], a decision tree describes the process graphically and simplifies a major goal of the analysis – to determine the best decisions. In addition to the traditional approaches mentioned above, in this research we investigate comparatively non-popular nowadays, but prospective method – evolutionary algorithm. In [5] it is underlined, that this approach is based on the evolution of set of rules genetically codified. Overall, despite all three methods are applied to a wide range of decision making processes, in this study we compare the potential, effectiveness and quality of forecasting for universal problems.

In this paper we preliminarily analyze approaches to solve the task of sales forecasting. The actual task is to estimate the efficiency of marketing campaigns with the goal to advertise and deliver (or push) the product to the market. These activities are the means to increase the sales. So, if we could predict the sales of some product in advance and then compare it with the actual data, we can fix the profitability of marketing campaigns conducted.

In our review we will not analyze method combinations, sequentially applied nor parallel, though it worth attention. But we concentrate attention on basic approaches and fix the a-priori advantages and disadvantages of each. We will revert and compare our conclusions with new, ad hoc, results after application of them to real-life data.

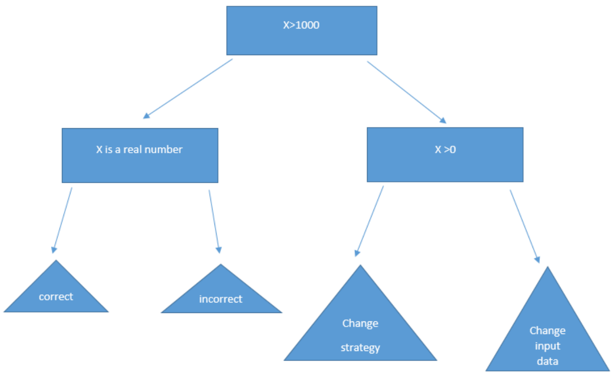
Problem Formalization

The predictive methods make forecast based on the statistical relationships between input columns in a dataset. The major idea is to interpret current data in a proper way in order to obtain the objective laws. Input data is represented by a dataset. In our formulation three basic categories are considered to be processed: product name, sales and period under consideration. In order to facilitate the perception of forecasting model, we investigate the case of the one product name. The predictive approaches are applied to a dataset to obtain a probable prognosis for the future period.

We discuss Decision Trees approach, Evolutionary or genetic algorithms class and compare them to Microsoft Time Series algorithm, the practical realization of known methods.

Decision Trees Method

A decision tree is a drawing [6], consisting of lines and boxes, that shows the different choices which are available to people before they make a decision, and the possible results of these choices. According to [7], decision trees are produced by algorithms that identify various ways of splitting a data set into branch-like segments. These segments form an inverted decision tree that originates with a root node at the top of the tree. It is mentioned in [8], that graphically a decision tree looks like a flowchart-like structure in which each internal node represents a “test” on an attribute. Commonly a decision tree consists of three types of nodes: decision nodes (represented by squares), chance nodes (represented by circles) and end nodes (represented by triangles). According to [9] it is also easier for many to read and understand flow chart symbols mentioned above. Classification and regression trees were originally introduces and investigated by Breiman [10] in 1984. As asserted in [11], the main idea behind tree methods is to recursively partition the data into smaller and smaller strata in order to improve the fit as best as possible. Tree models where the target variable can take a finite set of values are called classification trees. Decision trees where the target variable can take continuous values (typically real numbers) are called regression trees [12]. As explained in [13], that classification trees are designed for dependent variables that take a finite number of unordered values, with prediction error measured in terms of misclassification cost. Regression trees are for dependent variables that take continuous or ordered discrete values, with prediction error typically measured by the squared difference between the observed and predicted values.



Picture 1. *Decision Tree*.

In CART (classification and regression tree) data are handled in their raw form; no binning is required or recommended [14]. In our model data is represented by a training sample of $\boldsymbol{n}$ observations on a variable Y, which represent sales, and $\boldsymbol{m}$ variables, X_1 ,..., X_m, which represent time period. A major aim is to find a model for predicting the values of Y for new periods. Classical algorithm generates a model by building a series of tree splits (traditionally nodes serve as representations of these splits). A node is added to the ultimate model every time that an element of Y-dataset substantially influences the predictable column ($Y_{n+1}, \dots Y_{n+k}$, where $\boldsymbol{k}$ – is a predictable period). It is worth noting, that data required for the forecasting also includes a key basic category that serves as identificator. In our study we use a product name for these purposes.

CART splitting rules [14] are represented by the following construction:

$$An\ instance\ goes\ left\ if\ CONDITION,\ otherwise\ goes\ right.$$

General algorithm includes the following steps:

1) Start at the root node.
2) To each X_i, apply a condition split
3) If a stopping criterion is reached, exit. Otherwise, apply step 2 to each child node in turn.

Evolutionary Algorithm

According to [15] the term "genetic and evolutionary algorithms" is used to name a family of computational procedures where a number of potential solutions to a problem makes the way to an evolving population. Before a genetic algorithm can be put to work on any problem, a method is needed to encode potential solutions to that problem in a form that a computer can process. One common approach is to encode solutions as binary strings: sequences of 1's and 0's, where the digit at each position represents the value of some aspect of the solution [18]. Each individual codes a solution in a string (chromosome) of symbols (genes), being assigned a numerical value (fitness function), that stands for a solution quality`s measure. New solutions are created as a result of application of operators to the current solutions. There are three main operators are widely used: mutation, crossover and selection. The main effect of mutation is to invert a bit in a chromosome [16]. In [17] it is supposed a chromosome:

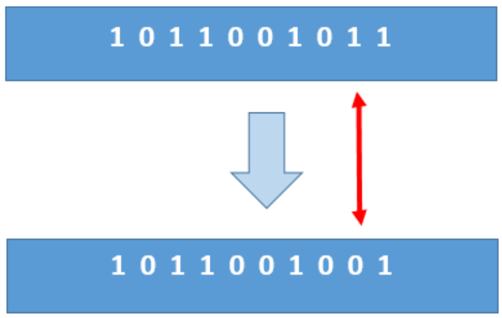
$$S_1 = \{s_{11}, s_{12}, \dots, s_{1n}\}.$$

Select a random integer number:

$$0 \le r \le n.$$

S_2 is a mutation of S_1 in this case:

$$S_2 = \{s_i | \, if\ i \ne r\ \ then\ s_i = s_{1i}\ else\ s_i = random(s_{1i})\}.$$



Picture 2. *Mutation in genetic algorithm.*

Crossover causes exchange of bits string between two chromosomes [16], [17]. Two chromosomes are supposed:

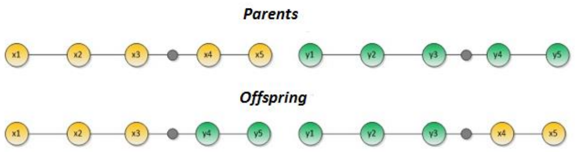
$$S_1 = \{s_{11}, s_{12}, \dots, s_{1n}\}$$
$$S_2 = \{s_{21}, s_{22}, \dots, s_{1n}\}$$

Then select a random integer number:

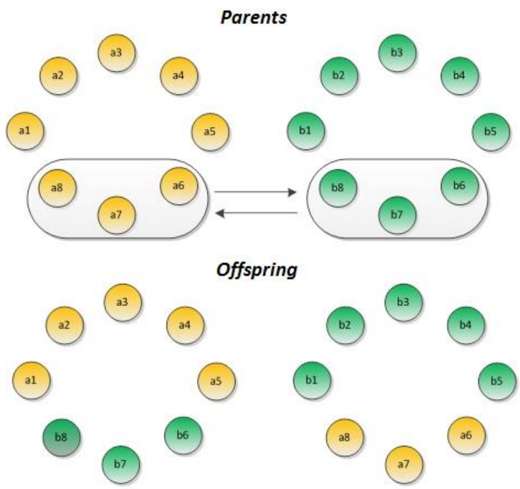
$$0 \leq r \leq n.$$

S_3,S_4 are offspring of S_1 and S_2 crossover in this case:

$$S_3 = \{s_i | \, if \; i \leq r, s_i \subset S_1, else \; s_i \subset S_2\}.$$
$$S_4 = \{s_i | \, if \; i \leq r, s_i \subset S_2, else \; s_i \subset S_1\}.$$



Picture 3. *Crossover in genetic algorithm.*



Picture 4.*Crossover in genetic algorithm.*

As it is mentioned in [17], in selection operator we suppose there are ***m*** individuals, we select [m/2] individuals but erase the others, the ones we selected are "more fitness" that means their profits are greater.

The basic steps of the genetic algorithm involve:

1) Initialization of start population
2) Test of the stopping ctiteria. If it is false – continue, else – stop.
3) Mutation operator application
4) Crossover operator application
5) Selection procedure (choosing the best chromosomes).

When it comes to practical applications, in [16] it is highly recommended to estimate the scope of the parameters domain in order to make genetic algorithm search more effective. It is proposed to use heuristic knowledge about the explored demand. In our study it namely means to set amplitude for sales (minimum and maximum level). In our case we concentrate on predictive analysis. Observations are represented by a dataset, so, the main idea is to test input data with the usage of various operators in order to find the correlation between operators and predictive results. We must note here, that originally evolutionary algorithms were constructed for optimization tasks that is why this approach is principally different from the algorithms mentioned above. This method is completely dependent on the operators. Nevertheless, this fact enables to take into consideration the influence of external factors, which is significant for the problem of forecasting. For our particular case classic genetic algorithm is slightly modified. Initialization procedure is more clear: there is no necessity to generate a random dataset.

Time Series Analysis

The Microsoft Time Series Algorithm provides regression algorithms that are optimized for the forecasting of continuous values, such as product sales, over time. Whereas other Microsoft algorithms, such as decision trees, require additional columns of new information as input to predict a trend, a time series model does not. A time series model can predict trends based only on the original dataset that is used to create the model. You can also add new data to the model when you make a prediction and automatically incorporate the new data in the trend analysis [3].

The Microsoft Time Series algorithm includes two separate algorithms for analyzing time series:

1) The ARTXP (short for Auto Regression Trees with Cross Predict) [20] algorithm, which was introduced in SQL Server 2005, is optimized for predicting the next likely value in a series.

2) The ARIMA algorithm was added in SQL Server 2008 to improve accuracy for long-term prediction.

By default, Analysis Services uses each algorithm separately to train the model and then blends the results to yield the best prediction for a variable number of predictions. You can also choose to use just one of the algorithms, based on your data and prediction requirements [3].

Microsoft Research developed the original

ARTXP algorithm that was used in SQL Server 2005, basing the implementation on the Microsoft Decision Trees algorithm. Therefore, the ARTXP algorithm can be described as an autoregressive tree model for representing periodic time series data. This algorithm relates a variable number of past items to each current item that is being predicted [3].

The ARIMA algorithm was added to the Microsoft Time Series algorithm in SQL Server 2008 to improve long-term prediction. It is an implementation of the process for computing autoregressive integrated moving averages that was described by Box and Jenkins. The ARIMA methodology makes it possible to determine dependencies in observations taken sequentially in time, and can incorporate random shocks as part of the model. The ARIMA method also supports multiplicative seasonality [3].

By default, the Microsoft Time Series algorithm uses both methods, ARTXP and ARIMA, and blends the results to improve prediction accuracy. If you want to use only a specific method, you can set the algorithm parameters to use only ARTXP or only ARIMA, or to control how the results of the algorithms are combined [3].

Advantages and disadvantages of decision trees

The benefits of the usage of decision trees are rather obvious:

1) The model is having a single meaning; the process is well-defined and stepwise. This approach is clear for both understanding and implementation. Decision trees are simple to understand and interpret.

2) The tree anticipates the dead ends and there is no problem with stopping criteria (in comparison with evolutionary algorithms).

3) In [22] it is noticed, that decision trees require relatively little effort from users for data preparation. Moreover, it is worth noting, this approach is also able to cope with different types of data. In this research we work with only numerical data, nevertheless, in more complicated cases, this aspect may presuppose the choice of algorithm.

The most substantial disadvantages are the following:

1) The prediction is defined just once; all the consequences are based on the previous experience. It is mentioned in [21], that the reliability of the information in the decision tee depends on feeding the precise internal and external information at the onset. Even a small change in input data can at times, cause large changes in the tree. Changing variables, excluding duplication information, or altering the sequence midway can lead to major changes and might possibly require redrawing the tree.

2) As [21] states, another fundamental flaw of the decision tree prognosis is that the decisions contained in the decision tree are based on expectations, and irrational expectations can lead to flaws and errors in the decision tree. Although the decision tree follows a natural course of events by tracing relationships between events, it may not be possible to plan for all contingencies that arise from a decision, and such oversights can lead to bad decisions.

Advantages and disadvantages of genetic algorithm

The major advantages of the genetic algorithm are:

1) The vitally important point is that genetic algorithms are intrinsically parallel. Most other algorithms are serial and can only explore the solution space to a problem in one direction at a time, and if the solution they discover turns out to be suboptimal, there is nothing to do but abandon all work previously completed and start over. Genetic algorithms are able to explore the solution space in multiple directions at once. If one path turns out to be a dead end, they can easily eliminate it and continue work on more promising avenues, giving them a greater chance each run of finding the optimal solution [18]. This fact is particularly significant especially for our case owing to the colossal perspective amount of input data.

2) Another notable strength of genetic algorithms is that they perform well in problems for which the fitness landscape is complex – ones where the fitness function is discontinuous, noisy, changes over time, or has many local optima [18]. Many search algorithms can become trapped by local optima: if they reach the top of a hill on the fitness landscape, they will discover that no better solutions exist nearby and conclude that they have reached the best one, even though higher peaks exist elsewhere on the map. Evolutionary algorithms, on the other hand, have proven to be effective at escaping local optima and discovering the global optimum in even a very rugged and complex fitness landscape. This aspect is

also substantial for our problem due to the fact that such category as "desirable sales" may be changed during the period.

The main disadvantages are the following:

1) A drawback of any evolutionary algorithm is that a solution is "better" only in comparison to other, presently known solutions; such an algorithm actually has no concept of an "optimal solution," or any way to test whether a solution is optimal (for this reason, evolutionary algorithms are best employed on problems where it is difficult or impossible to test for optimality) [19]. This also means that an evolutionary algorithm never knows for certain when to stop, aside from the length of time, or the number of iterations or candidate solutions, that you wish to allow it to explore. Nevertheless, this factor is acceptable when it comes to our study because period of time is always known beforehand. In addition to this, the main goal is forecasting based on the previous data, and genetic algorithm is applicable to this problem better than to optimization.

2) Anyway, to find a stopping condition is not a trivial task. That is why the number of iterations is traditionally serves instead of it. In general, it may lead to worse solutions. It is not as crucial in our problem of prognosis as in the widespread problem of optimization, but, definitely, it may deteriorate the computational accuracy. Steven S. Skiena, in [20] strictly disbelieves in genetic approach and suggests that there is no clear problem which may be resolved with the usage of this algorithm even conditionally optimal.

Advantages and disadvantages of Microsoft Time Series Algorithm

Taking into account that this algorithm is "closed-source" and comes "out of the box", it is ready to use and we can quickly start applying it to the raw data. But the limitation is that we can manipulate only allowed parameter values and this defines its pros & cons. As a Microsoft's concrete realization of Decision Trees concept at high level, this approach inherits advantages and disadvantages of Decision Trees approach as well.

If we analyze two built-in models inside this approach, namely ARIMA and ARTXP, then advantages and disadvantages can be presented in the following form:

ARIMA model pros:
1. Good for long-term prediction.
2. Supports multiplicative seasonality.
3. Combines autoregression.
4. Well-known model, checked over time.

ARIMA model cons:
1. Not possible to run policy simulation.
2. Traditional model identification techniques are subjective.
3. Does not support cross-prediction.

ARTXP model pros:
1. Supports cross-prediction.
2. Gives appropriate predictions in the near future.
3. Better to look at different variables influencing each other over time.

ARTXP model cons:
1. Less stable.
2. Not appropriate for long-term prediction.
3. High complexity of calculations for long-term predictions (requires much more time).

Conclusion

In this paper we investigated most appropriate a-priory methods for the task of product sales forecasting by known sales history and without other factors influence. This represents real-life practical task when we cannot use factor analysis and must rely on historical data solely.

We fixed

- Decision Trees with Random Forests approach,
- Evolutionary and Genetic algorithms and
- Microsoft Time Series Algorithm (realization)

as most appropriate (a-priory) for the task stated and discussed these methods here.

Advantages and disadvantages of each of them were shown and argued in details.

The next step is to apply all the methods to real-life data, i.e. real production sales historical data, tune the models and then analyze and compare a-priory with a-posteriori results to make the final decision about methods applicability as well as results obtained in each case.

Список використаних джерел

1. *Чугуева И.А.* Модель прогрозирования временних рядов по выборке максимального подобия. Дисертация на соискание ученой степени кандидата технических наук.: 05.13.18 / И.А. Чугуева. – М., 2012. – 153 с.
2. *Geisser S*. Predictive Inference: An Introduction. Monographs on Statistics and Applied Probability / S. Geisser. – NY: Chapman & Hall, 1993. – 265 p.
3. Microsoft Developer Network, Available from: <www.msdn.com>.
4. *TreePlan Software*. Introduction to Decision Trees. Available from: <http://treeplan.com/ chapters/introduction-to-decision-trees.pdf>.
5. *del Arco-Calderón C.L*. Forecasting Time Series by Means of Evolutionary Algorithms / C.L. del Arco-Calderón, P.I. Viñuela, J.C.H. Castro // Parallel Problem Solving from Nature – PPSN VIII, Berlin, Springer Berlin Heidelberg, LNCS. – 2004. – Vol.3242. – pp. 1061-1070.
6. Cambridge Dictionaries Online: English Dictionary. Available from: <http://dictionary. cambridge.org/dictionary/english/decision-tree>.
7. *SAS Institute*. Decision Trees – What Are They? Available from: <http://support.sas.com/ publishing/pubcat/chaps/57587.pdf>.
8. *Pandey A.K*. Early Software Reliability Prediction: A Fuzzy Logic Approach / A.K. Pandey, N.K. Goyal. – New Dehli: Springer India, 2013. – 153 p.
9. *Xu G*. Applied Data Mining / Guandong Xu, Yu Zong, Zhenglu Yang.–CRC Press, 2013.–284 p.
10. *Breiman L*. Classification and Regression Trees / L. Breiman, J. Friedman, C.J. Stone, R.A. Olshen. – Chapman and Hall/CRC, 1984.–368 p.
11. *Gordon L*. Using Classification and Regression Trees (CART) in SAS Enterprise Miner For Applications in Public Health / Leonard Gordon // SAS Global Forum 2013. Paper 089-2013. – 2013. – 8 p.
12. *Jopp F*. Modelling Complex Ecological Dynamics: An Introduction into Ecological Modelling for Students, Teachers & Scientists / F. Jopp, H. Reuter, B. Breckling (Eds.). – Springer-Verlag Berlin Heidelberg, 2011.–397 p.
13. *Loh W.-Y*. Classification And Regression Trees / W.-Y. Loh // WIREs Data Mining and Knowledge Discovery.–2011.–Vol.1.–pp.14-23.

References

1. CHUGUEVA, I. (2012) *Time Series Forecasting Model by Maximal Similarity Sample* (PhD Thesis). Moscow. 153 p.
2. GEISSER, S. (1993) *Predictive inference: an introduction. Monographs on Statistics and Applied Probability*. NY, Chapman&Hall. 265 p.
3. Microsoft Developer Network, Available from: <www.msdn.com>.
4. TreePlan Software. *Introduction to Decision Trees*. Available from: <http://treeplan.com/ chapters/introduction-to-decision-trees.pdf>.
5. Del ARCO-CALDERÓN, C.L., VIÑUELA, P.I. and CASTRO J.C.H. (2004) Forecasting Time Series by Means of Evolutionary Algorithms. *Parallel Problem Solving from Nature – PPSN* VIII. LNCS, Springer Berlin Heidelberg, Vol.3242. pp. 1061-1070.
6. Cambridge Dictionaries Online: English Dictionary. Available from: <http://dictionary. cambridge.org/dictionary/english/decision-tree>.
7. SAS Institute. Decision Trees – What Are They? Available from: <http://support.sas.com/ publishing/pubcat/chaps/57587.pdf>.
8. PANDEY, A.K. and GOYAL, N.K. (2013) *Early Software Reliability Prediction: A Fuzzy Logic Approach*. New Dehli: Springer India. 153 p.
9. XU, G., ZONG, Yu and YANG, Zh. (2013) *Applied Data Mining*. CRC Press. 284 p.
10. BREIMAN, L., FRIEDMAN, J., STONE, C.J. and OLSHEN, R.A. (1984) *Classification and Regression Trees*. Chapman and Hall/CRC. 368 p.
11. GORDON, L. (2013) Using Classification and Regression Trees (CART) in SAS Enterprise Miner For Applications in Public Health. *SAS Global Forum 2013*. Paper 089-2013. 8 p.
12. JOPP F., REUTER, H. and BRECKLING, B., Eds. (2011) *Modelling Complex Ecological Dynamics: An Introduction into Ecological Modelling for Students, Teachers & Scientists*. Springer-Verlag Berlin Heidelberg. 397 p.
13. LOH W.-Y. (2011) Classification and regression trees. *WIREs Data Mining and Knowledge Discovery*, Vol.1. pp. 14-23.
14. WU, X., KUMAR, V., QUINLAN, J.R., GHOSH, J., et al. (2008) Top 10 algorithms in data mining. *Knowledge and Information Systems*, Vol.14, issue 1. pp. 1-37.

14. *Wu X.* Top 10 Algorithms In Data Mining / Xindong Wu, Vipin Kumar, J. Ross Quinlan, Joydeep Ghosh, Qiang Yang, Hiroshi Motoda, Geoffrey J. McLachlan, Angus Ng, Bing Liu, Philip S. Yu, Zhi-Hua Zhou, Michael Steinbach, David J. Hand, Dan Steinberg // Knowledge and Information Systems. – 2008. – Vol.14, Iss.1. – pp.1-37.
15. *Cortez P.* Genetic and Evolutionary Algorithms for Time Series Forecasting / Paulo Cortez, Miguel Rocha, José Neves // Engineering of Intelligent Systems, Proceedings of 14th International Conference on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems, IEA/AIE 2001 Budapest, Hungary, June 4–7, 2001. – Springer Berlin Heidelberg, 2001. – LNCS, Vol.2070. – pp.393-402.
16. *Chodak G.* Genetic Algorithms in Seasonal Demand Forecasting / Chodak Grzegorz, Kwaśnicki Witold // In Proceedings of "Information Systems Architecture and Technology '2000, Wrocław University of Technology". – Wrocław, 2000. – pp.91-98.
17. *Lin L.* The applications of genetic algorithms in stock market data mining optimisation / L. Lin, L. Cao, J. Wang & C. Zhang // Proceedings of Fifth International Conference on Data Mining, Text Mining and their Business Applications (September 15-17, 2004, Malaga, Spain). – Southampton, Boston: WITPress, 2004.–pp.273-280.
18. *Marczyk A.* Genetic Algorithms and Evolutionary Computation / Adam Marczyk. – The TalkOrigins Archive 2004. – 2004. Available from: <www.talkorigins.org/faqs/genalg/genalg.html>.
19. *FrontlineSolvers.* Genetic Algorithms And Evolutionary Algorithms – Introduction. Available from: <http://www.solver.com/genetic-evolutionary-introduction>.
20. *Skiena S.* The Algorithm Design Manual / Steven S. Skiena. – London: Springer-Verlag, 2008. – 730 p.
21. *Bright Hub Project Management.* Disadvantages to Using Decision Trees. Available from: <http://www.brighthubpm.com/project-planning/106005-disadvantages-to-using-decision-trees/>.
22. *Deshpande B.* 4 key advantages of using decision trees for predictive analytics / Bala Deshpande. Available from: <www.simafore.com/blog/bid/62333/4-key-advantages-of-using-decision-trees-for-predictive-analytics>.

15. CORTEZ, P., ROCHA, M. and NEVES, J. (2001) Genetic and Evolutionary Algorithms for Time Series Forecasting. *Engineering of Intelligent Systems, Proceedings of 14th International Conference on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems, IEA/AIE* 2001 Budapest, Hungary, June 4–7, 2001. Springer Berlin Heidelberg, LNCS, Vol.2070. pp.393-402.
16. CHODAK, G. and KWAŚNICKI, W. (2000) Genetic Algorithms in Seasonal Demand Forecasting. *Proceedings of "Information Systems Architecture and Technology '2000"*, Wrocław University of Technology, Wrocław. pp. 91-98.
17. LIN, L., CAO, L., WANG, J. and ZHANG, C. (2004) The applications of genetic algorithms in stock market data mining optimisation. *Proceedings of Fifth International Conference on Data Mining, Text Mining and their Business Applications* (September 15-17, 2004, Malaga, Spain). Southampton, Boston, WITPress. pp.273-280.
18. MARCZYK, A. (2004) *Genetic Algorithms and Evolutionary Computation*. The TalkOrigins Archive 2004. Available from: <http://www.talkorigins.org/faqs/genalg/genalg.html>.
19. FrontlineSolvers. *Genetic Algorithms And Evolutionary Algorithms – Introduction*. Available from: <http://www.solver.com/genetic-evolutionary-introduction>.
20. SKIENA, S. (2008) *The Algorithm Design Manual*. London: Springer-Verlag. 730 p.
21. Bright Hub Project Management. *Disadvantages to Using Decision Trees*. Available from: <http://www.brighthubpm.com/project-planning/106005-disadvantages-to-using-decision-trees/>.
22. DESHPANDE, B. *4 key advantages of using decision trees for predictive analytics*. Available from: <http://www.simafore.com/blog/bid/62333/4-key-advantages-of-using-decision-trees-for-predictive-analytics>.

Надійшла до редколегії 10.09.2015