

Chapter 7

An Enhanced Artificial Bee Colony Optimizer for Predictive Analysis of Heating Oil Prices using Least Squares Support Vector Machines

Zuriani Mustaffa

Universiti Utara Malaysia (UUM), Malaysia

Yuhanis Yusof

Universiti Utara Malaysia (UUM), Malaysia

Siti Sakira Kamaruddin

Universiti Utara Malaysia (UUM), Malaysia

ABSTRACT

As energy fuels play a significant role in many parts of human life, it is of great importance to have an effective price predictive analysis. In this chapter, the hybridization of Least Squares Support Vector Machines (LSSVM) with an enhanced Artificial Bee Colony (eABC) is proposed to meet the challenge. The eABC, which serves as an optimization tool for LSSVM, is enhanced by two types of mutations, namely the Levy mutation and the conventional mutation. The Levy mutation is introduced to keep the model from falling into local minimum while the conventional mutation prevents the model from over-fitting and/or under-fitting during learning. Later, the predictive analysis is followed by the LSSVM. Realized in predictive analysis of heating oil prices, the empirical findings not only manifest the superiority of eABC-LSSVM in prediction accuracy but also poses an advantage to escape from premature convergence.

DOI: 10.4018/978-1-4666-6078-6.ch007

INTRODUCTION

Over the last decades, there has been a growing interest in energy fuel price predictive analysis and this issue attracts the attention not only from practitioners but also the scientific community. Due to its significant non linearity characteristic, this issue is regarded as challenging task and received an impressive interest from time to time (Tehrani & Khodayar, 2011). In literature, considerable amount of studies on predictive analysis have been published, spanning from conventional statistical techniques to Computational Intelligence (CI) approach. Nonetheless, the obvious non linearity of energy fuel prices makes the conventional statistical techniques such as Autoregressive Integrated Moving Average (ARIMA) (Yusof, Rashid, & Mohamed, 2010) inapplicable. Such situation has led the academia to heed an attention on CI approach, which includes Artificial Neural Network (ANN) (Kulkarni & Haidar, 2009), Support Vector Machines (SVM) (Khashman & Nwulu, 2011) and also Least Squares Support Vector Machines (LSSVM) (Bao, Zhang, Yu, Lai, & Wang, 2011). As a derived version of conventional SVM (Vapnik, 1995), the LSSVM (Suykens, Van Gestel, De Brabanter, De Moor, & Vandewalle, 2002) provides an efficient learning algorithm which offers promising generalization (i.e. the ability of hypothesis to correctly predict on unseen data set) capability. With the adaptation of Structural Risk Minimization (SRM) principle, LSSVM seems to be a good candidate in addressing the over fitting problem which is found in ANN (Xiang & Jiang, 2009). Unlike Empirical Risk Minimization (ERM) which is adopted in ANN, the SRM principle tends to minimize an upper bound of generalization error rather than training error as applied in ERM (Afshin, Sadeghian, & Raahemifar, 2007). This characteristic equips the LSSVM with a great ability for generalization. With such an interesting feature, the application of LSSVM has been broadly utilized in various fields such as classification (Luts, Molenberghs, Verbeke, Van

Huffel, & Suykens, 2012), prediction (Zhai & Huang, 2013) and many others. The remarkable performance of LSSVM has also attracted communities from different area includes engineering (Wu & Niu, 2009), finance (Shen, Zhang, & Ma, 2009), meteorological (Mellit, Massi Pavan, & Benghanem, 2013) so on so forth.

Even though LSSVM comes with such an interesting property, the performance of LSSVM greatly relies on the value of hyper-parameters, namely regularization parameter, γ and kernel parameter, σ^2 . Both hyper parameters values will directly affect the regression accuracy and generalization of LSSVM. As to resolve this problem, in literature, it is observed that there are two common approaches in optimizing the LSSVM hyper-parameters; experimental technique and theoretical technique (Afshin, et al., 2007). In experimental technique, the Cross Validation (CV) (Afshin, et al, 2007; Mellit, et al., 2013) is commonly utilized. However, since CV requires an exhaustive search over the parameter space, in term of time, it is inefficient (Zhang, Niu, Li, & Li, 2013). In addition, the obtained error rates tend to be unsatisfactory (Yu, Chen, Wang, & Lai, 2009). On the other hand, the latter approach involved the hybridization of LSSVM with various theoretical Evolutionary Computation (EC) algorithm, such as Genetic Algorithm (GA) (Haupt & Haupt, 2004) which is developed based on natural selection (Liao & Balzen, 2013) and Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995) which based on analogy of bird flocking and fish schooling. However, this field is still widely open for improvement as currently there exists a few others EC algorithm. Hence, the aim of this study is to utilize Artificial Bee Colony which was introduced in 2005 to optimize the algorithmic parameters of LSSVM. The ABC algorithm is inspired from the foraging behavior of honey bees swarm (Karaboga, 2005). The unique of ABC can be seen in the number of algorithmic parameters which is smaller compared to GA and PSO. Apart of two fundamental control parameters

23 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:
www.igi-global.com/chapter/an-enhanced-artificial-bee-colony-optimizer-for-predictive-analysis-of-heating-oil-prices-using-least-squares-support-vector-machines/110458

Related Content

Experimental Study I: Automobile Dataset

(2018). *Predictive Analysis on Large Data for Actionable Knowledge: Emerging Research and Opportunities* (pp. 91-110).

www.irma-international.org/chapter/experimental-study-i/196390

Temporal Association Rule Mining in Large Databases

A. V. Senthil Kumar, Adnan Alrabea and Pdamallu Chandra Sekhar (2013). *Data Mining: Concepts, Methodologies, Tools, and Applications* (pp. 586-602).

www.irma-international.org/chapter/temporal-association-rule-mining-large/73459

A Unified Multi-View Clustering Method Based on Non-Negative Matrix Factorization for Cancer Subtyping

Zhanpeng Huang, Jiekang Wu, Jinlin Wang, Yu Lin and Xiaohua Chen (2023). *International Journal of Data Warehousing and Mining* (pp. 1-19).

www.irma-international.org/article/a-unified-multi-view-clustering-method-based-on-non-negative-matrix-factorization-for-cancer-subtyping/319956

Assistance of Internet of Things to Intelligent Business Management Model of Supply Chain Finance and Modern Logistics Enterprises

Qing Li (2023). *International Journal of Data Warehousing and Mining* (pp. 1-17).

www.irma-international.org/article/assistance-of-internet-of-things-to-intelligent-business-management-model-of-supply-chain-finance-and-modern-logistics-enterprises/323189

Information Visualization and Policy Modeling

Kawa Nazemi, Martin Steiger, Dirk Burkhardt and Jörn Kohlhammer (2016). *Big Data: Concepts, Methodologies, Tools, and Applications* (pp. 139-180).

www.irma-international.org/chapter/information-visualization-and-policy-modeling/150163