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# Support vector regression modelling and optimization of energy consumption in carbon fiber production line

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ABSTRACT

The main chemical industrial efforts are to systematically and continuously explore innovative computing methods of optimizing manufacturing processes to provide better production quality with lowest cost. Carbon fiber industry is one of the industries seeks these methods as it provides high production quality while consuming a lot of energy and being costly. This is due to the fact that the thermal stabilization process consumes a considerable amount of energy. Hence, the aim of this study is to develop an intelligent predictive model for energy consumption in thermal stabilization process, considering production quality and controlling stochastic defects. The developed and optimized support vector regression (SVR) prediction model combined with genetic algorithm (GA) optimizer yielded a very satisfactory set-up, reducing the energy consumption by up to 43%, under both physical property and skin-core defect constraints. The developed stochastic-SVR-GA approach with limited training data-set offers reduction of energy consumption for similar chemical industries, including carbon fiber manufacturing.


## 1. Introduction

Industries account for a large part of energy consumption (Gielen and Taylor, 2009; Sahin and Koksal, 2014) and they face major challenges for energy and cost saving (Cai et al., 2009a; Han et al., 2016; Kermani et al., 2017; Lin et al., 2010). Hence, developing intelligent methodologies to manage energy and cost has great benefit for manufacturers. Carbon fiber industries are not exempt from this matter. Over the past several years, carbon fibers have been extensively used as a high-strength and high performance material in high technology sectors including aerospace, automotive, aviation, nuclear engineering, transportation sectors, marines, among others (Chand, 2000). Due to its light weight, high tensile strength, superior Young's modulus, low density and high toughness (Karacan and Erdoğan, 2012a), carbon fiber is perfectly appropriate for applications where the aforementioned properties play a critical role. About 90% of carbon fibers produced today are derived from polyacrylonitrile (PAN) fiber precursor. Three major steps are involved in production of carbon fiber with stabilization step being considered as the most complex, non-linear, energy consuming, expensive and time-consuming step (Zhu et al., 2003). Stabilization time, temperature and tension (stretching ratio) (TTT) are the main operating parameters in the thermal oxidative stabilization process (Badii et al., 2014; Khayyam et al., 2015b). The stabilization step accounts for 18% of the total cost of PAN-based carbon fiber production and 63% of the total energy consumption in a single tow pilot plant (Badii et al., 2016); therefore, low-cost thermal stabilization process is necessary in mass-scale production settings by reducing energy (Pintarič and Kravanja, 2015).

During process optimization (in particular energy), the stabilization should be evaluated as a nonlinear complex chemical-physical system due to the presence of multiple operating and design parameters (at least 14 parameters) (Badii et al., 2014), sensitivity to external environment, and the ambiguity in their connections (parameter interactions) (Karacan and Erdoğan, 2012a).

It is vital to take into account the production quality and economic objectives by including those in the optimization criteria when optimizing energy in stabilization process. In order to improve the quality of the product, physical property (density) should be considered in the energy optimization of the process.

To produce carbon fibers with superior mechanical properties, an optimal density is desirable (Karacan and Erdoğan, 2012b), and

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higher density results in more stable fiber (Jing et al., 2008). Due to such high effect, it has become common to use density as a progress indicator of stabilization process (Gupta and Harrison, 1996; Karacan, 2012).

In order to optimize the energy consumption based on a given desired range of density, the first step is to develop a mathematical relationship between density and operating parameters. A large number of experiments, however, are needed to find the relationship between main operating parameters and density, which is often costly and time consuming (Badii et al., 2016). Furthermore, conducting experiments for all the process parameters is not practically possible due to project times and technical constraints in industry.

To avoid performing expensive experimental optimization, a powerful approach is the use of intelligent predictive surrogate models (Lin et al., 2010). In recent years, the developments in intelligent methods make them possible to be used in complex systems (Khayyam et al., 2017a; Khayyam et al., 2015b). According to the "No Free Lunch" theorem (Wolpert and Macready, 1997), no model exists that works best for every problem and it is impossible to develop an optimization method that is universally better than all others. As a result, it is common in machine learning to try multiple models and find one that works best for a particular problem (Balabin and Lomakina, 2011; Khayyam et al., 2015b). The accuracy of different prediction methods is often examined by comparing them with far less experimental test data. Results of the top ranked predictive model can then be further used for the optimization. In order to develop a model for physical property in this study, the predictive models were developed using artificial neural network (ANN) and support vector regression (SVR) methods.

On the other hand, in order to avoid structural defect (skin-core defect) which forms during stabilization process, it should also be considered as a criterion while optimizing energy consumption. Skin-core defect reduces the homogeneity of the fiber and causes structural flaws (Liu et al., 2014; Lv et al., 2009). It is one of the most prominent factors affecting the mechanical properties of the produced carbon fiber. In order to describe the stochastic relationship between the skin-core defect and the operating parameters of the fiber production, previous study was considered (Golkarnarenji et al., 2017).

There are a limited body of works carried out on chemical, physical and mechanical properties of OPF (Oxidized Polyacrylonitrile Fiber) and carbon fiber. Khayyam et al. (Khayyam et al., 2015b) studied and analyzed the carbon fiber thermal stabilization process through dynamic models for prediction of the process. Taylor polynomial method, Gauss-Newton algorithm (GNA), Levenberg-Marquardt algorithm (LMA) neural network, and genetic algorithm (GA) were the methods employed and compared. The results indicated that a given PAN fiber heat of reaction can be optimized based on appropriate values of temperature and heating ramp. Khayyam et al. (Khayyam et al., 2015a) also developed a stochastic optimization for energy management in carbonization process of carbon fiber production line. Based on their study, it is possible to predict the production quality and minimize the energy consumption of its industrial process with stochastic optimization models. Badii et al. (Badii et al., 2016) developed a model to predict density based on PAN precursor and OPF functional groups. However, estimation of applied rendering parameters is a difficult process and requires special expertise. Therefore, a simpler model based on operational parameters would be more practical, particularly for preliminary design purposes, line technicians and engineers.

In terms of energy consumption modelling, different approaches are available in literature such as engineering and data-driven approaches (Benedetti et al., 2016; Papadimitriou et al., 2014; Zhao and Magoulès, 2012; Zhao and Magoulès, 2010). Regarding predictive modelling for energy consumption in industrial processes, Kant and Sangwan (Kant and Sangwan, 2015) used ANN technique for model development for energy consumption in machining. The result showed that the predicted values were in good agreement with experimental data. The energy consumption level of ironmaking process was predicted using hybrid algorithm of support vector machine (SVM) and particle swarm optimization (PSO) (Zhang et al., 2012). In this study, the experimental tests are implemented based on the experimental data of a Chinese Iron and Steel Company. The result revealed a good accuracy in predicting the energy consumption of the particular ironmaking process. In another study, neural networks and SVM models were applied to optimize energy consumption in the primary stage of grinding process (Curilem et al., 2011). The result showed that using these black box models could bring benefits for complex industrial processes such as grinding process.

As artificial intelligent methods, like SVM and neural network, are the most accurate methods to predict and optimize energy consumption (Murray et al., 2016), SVR was used in this study to develop an energy model while the density and skin-core defect were the optimization criteria. By using a genetic algorithm as the optimizer, the optimization process revealed the optimal temperature, space velocity (inverse of residence time), and stretching ratio, while the least amount of energy was consumed. To the best of our knowledge, none of the aforementioned studies on energy optimization is based on density and skin-core defect constraints in a lab, pilot or industrial scale unit.

Industries such as carbon fiber manufacturers, would benefit from present study as it offers reduction of energy consumption and defects while improving production quality. Moreover, the intelligent predictive models such as SVR can be used in these industries to find the best operational parameters in order to potentially reduce the overall energy consumption and cost.

Hence, the main contributions/objectives of the present manuscript are:

1. To develop a novel intelligent predictive model for energy consumption with limited training data-set based on stochastic nature of stabilization process and uncertainty of the process.
2. To include a model for the skin-core effect as a stochastic defect during the optimization of energy consumption.
3. To develop a model for density to be considered in the energy consumption optimization.
4. To optimize the energy consumption in stabilization process based on the developed intelligent model for energy management and given range of Constrains such as fiber density and skin-core structural integrity.

The rest of this paper is organized as follows. In Section 2, materials and characterization of PAN precursor are presented. Section 3 discusses the energy management in stabilization process, different methods used to form the prediction models, and the validation and comparison of the methods. This is followed by skin-core effect modelling and the procedure for energy optimization. Section 4 presents the results of predictive models, energy consumption in stabilization process and its optimization. In Section 5, concluding remarks are presented.

## 2. Experimental procedure

### 2.1. Materials and equipment

The oxidative stabilization tests were carried out in a single tow oxidation pilot oven, designed by Despatch industries (also called carbon fiber research or CFR). Fig. 1 shows zone 1 of the pilot plant system. The PAN precursor used in the study was a commercial fiber