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Multi-Objective Optimization of Manufacturing Process in Carbon Fiber Industry Using Artificial Intelligence Techniques

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ABSTRACT Seeking high profitability by improving energy efficiency and production quality is the prime goal of manufacturing industries. However, achieving this aim involves the realization of several conflicting objectives. In carbon fiber industry, the stabilization process is the most vital step with high energy consumption. The aim of this study is to use intelligent modeling methods in the stabilization process to maximize energy efficiency while considering better production quality, avoiding defects, and not scarifying the prediction accuracy. To this aim, a modified DOE method was used to reduce the number of required experiments. The mechanical and physical properties were then modeled based on input-output data derived from the experiments. In this way, the SVR method is used to develop a set of mathematical models for mechanical and physical properties of the fibers. The skin-core defect and energy consumption were considered as objective functions within the given range of physical and mechanical properties of fibers. The state-of-the-art NSGA-II algorithm used to find the optimum Pareto front, including non-dominated solutions among these conflicting objective functions. The results showed that by using the integrated NSGA-II and technique for order preference by similarity to ideal solution (TOPSIS), the energy efficiency of the system was improved. Moreover, the discussions showed how similar hybrid algorithms with high accuracy can be used by other industries to reduce the overall energy consumptions.

INDEX TERMS Predictive models, manufacturing processes, multi-objective optimization, thermal stabilization, artificial intelligence, energy efficiency.

I. INTRODUCTION

Energy efficiency and production quality have become an increasingly important priority for manufacturing industries such as carbon fiber producers. However, satisfying these objectives simultaneously are highly complex in nature. Carbon fibers have been used in high technology sectors. Thermal stabilization process is the most non-linear, intricate, expensive and energy-intensive step in carbon fiber production process [1]–[4]. The complexity arises from the presence of multiple controlling parameters (at least 14 parameters) [5]. The significant parameters in the thermal stabilization process are Time, Temperature and Tension (TTT) [5], [6]. 63% of all consumption of energy in a pilot-scale, single tow line and 18% of the price of PAN fiber manufacturing is related to oxidative stabilization step; therefore, a low-cost oxidative stabilization process brings benefits for carbon fiber manufacturers [7]. This can be achieved by reducing the energy consumption. The optimization of the thermal stabilization process is time consuming and expensive as for each new precursor a substantial amount of tests is needed [2], [4], [6]. Furthermore, owing to technical constraints and project times in industry, experimental optimization is not virtually feasible. A powerful approach not to use experimental methods is using predictive models. These models are used to find a correlation between independent

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and dependent variables and predict the values of target variables [6]. They assist in optimization of the industrial processes [6], [8]–[11].

In this paper, to maximize production quality in stabilization process, models were developed for physical property (density) which indicates the progress of stabilization process and mechanical properties (tensile strength and Young's modulus). These models were then used as constraints to the optimization problem. To develop the predictive models for physical and mechanical properties of Oxidized PAN Fiber (OPF), the Support Vector Regression (SVR) method was used after being compared to ANN (Artificial neural network) model. Far less experimental tests are compared with the model predictions to examine the accuracy. The results of the predictive models were further used to define the decision space to decrease the energy consumption by optimizing the stabilization process. Skin-core defect which has a detrimental result on the mechanical properties of produced carbon fiber was considered as an objective in the optimization along with energy consumption to avoid defect. The developed model for skin-core defect were included in the optimization problem from previous study [12]. This multi-objective problem needs to be solved using intelligent global optimization techniques. Non-dominated Sorting Genetic Algorithm II (NSGA-II) was used as a fast, robust and effective intelligent method for this multi-objective optimization [13], [14]. Some studies have been done on physical, chemical and mechanical properties of carbon fiber and OPF (oxidized PAN fiber). In one study, various dynamic models were used for the optimization of heat of reaction related to PAN-based carbon fiber [6]. In another study the mechanical properties of carbon fiber were modelled for energy optimization in carbonization process [15]. A model was also developed based functional groups of oxidized PAN fiber for density [16]. In terms of modeling of energy consumption, there are also some studies in industrial processes [17]–[19]. In terms of multi objective optimization, some studies have also been done using NSGA-II [20]–[22]. In our understanding, none of the studies mentioned above, however, have covered multi-objective optimization of stabilization processes in an industrial scale unit with respect to physical and mechanical properties of fibers and associated defects. The developed procedure and models used in this paper can offer improvement of production quality while reducing energy consumption and skin-core defects for similar carbon fiber industries.

Hence, the specific objectives of this study are:

- To develop a new DOE with limited data set.
- To develop empirical models for mechanical properties (the Young's modulus and tensile strength) to be considered as a constraint for optimizing energy.
- To construct an empirical model for physical property (density) as a constraint for optimizing energy.
- Use the predictive models of thermal stabilization process for energy consumption and skin-core defect.
- To minimize skin-core defect and the energy consumption under constraints such as fiber mechanical and physical properties.

The schematic of the whole process has been illustrated in Fig. 1.

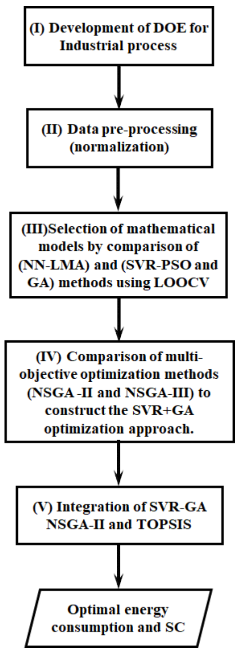


FIGURE 1. The followed procedure in the study.

This paper covers the following sections: Section II presents the materials and characterization of the employed PAN precursor. Section III presents the consumption of energy in stabilization process and the techniques used to develop and validate the predictive empirical models. This is followed by the procedure for energy optimization. Section IV, V and VI present the results of predictive models for physical and mechanical properties. Section VII covers the conclusion of the article.

II. MATERIALS AND EQUIPMENT

A terpolymer PAN precursor of acrylonitrile (>85%), itaconic acid (IA) and methyl acrylate (MA) (density: 1.1993 g/cm3 and linear density: 1.58 dtex) was provided through Blue Star enterprise. Based on Favimat test, the Young's Modulus and Tensile strength of PAN were 10.61GPa and 0.54GPa respectively.

A pilot-scale, single tow line from Despatch companies was used to perform the oxidative stabilization tests. Fig. 2 illustrates the Zone 1 of the single tow line. The change between speed of Drive 1 and 2 controls the stretching ratio of fiber.

The L16 Taguchi method (Table 1) was used to perform the experiments. Fiber space velocity of 20, 25, 30 and 35 m/h, temperature of 227, 230, 233, and 236° , and stretching-ratio of 1.0, 2.0, 3.0 and 4.0 % were chosen as the controlling parameters based on the feasible processing window of the

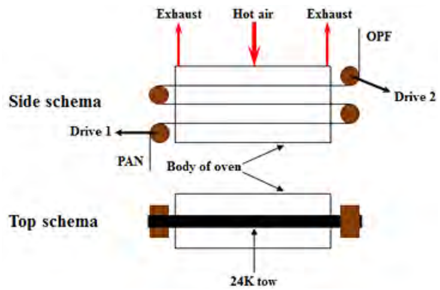


FIGURE 2. Schematic setup of pilot stabilization oven [12].

TABLE 1. Level of Operational Parameters.

Level	Temperature, °C	Space velocity, m/h	Stretching ratio, %
1	227	20	1.0
2	230	25	2.0
3	233	30	3.0
4	236	35	4.0

pilot plant. To reduce the number of experiments, the Taguchi design was modified by adding some marginal operating parameters.

The validity of the prediction models was checked with seven additional tests. Helium pycnometer (model Ultrapyc 1200e, Carbon Nexus, IFM, Deakin University) was used to measure the density of the samples. The mechanical properties of OPF were measured by FAVIMAT+ AIRobot2 single fiber tester (Carbon Nexus) in the single tow production line.

Since the filament variable is random, we expect to get different values as obtain multiple samples. Therefore, the probability distribution is used a magazine for different possible values of the random filament variable [23], [24]. The magazine of 25 samples was used to load filaments.

III. MANAGEMENT OF ENERGY IN STABILIZATION PROCESS

The sources that consume energy in thermal stabilization oven must be known to study the energy consumption. Recycling and exhaust fans, air electrical heater, drives 1,2 in the first oven (Fig. 3), and tow of PAN fiber [5], [6] consume energy.

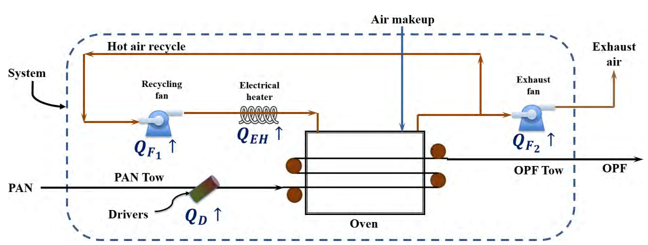


FIGURE 3. The sources for energy consumption in thermal stabilization production line [46].

Based on Fig. 3, Equation (1) demonstrates the energy consumption in stabilization process.

$$\begin{aligned} \textit{Energy consumption} &= E(T, S, \sigma) \\ &= Q_{F_1} + Q_{F_2} + Q_D + Q_{EH} \end{aligned} \tag{1}$$

IV. PREDICTIVE MODELS FOR PHYSICAL AND MECHANICAL PROPERTIES

To develop predictive empirical models for mechanical and physical properties, support vector regression as a predictive method was used. The support vector regression was compared to ANN (Artificial neural network) method to choose the best predictive model for physical and mechanical properties. The result indicated that this method is suitable to develop predictive models for physical and mechanical properties [25]. The predictive model developed for mechanical and physical properties was selected to be further used as constraints for multi-objective optimization purpose.

A. SUPPORT VECTOR REGRESSION (SVR)

Support Vector Machine (SVM) is one of the intelligent techniques based on structural risk minimization. It has many applications in regression and classification problems. Global optimal points can be obtained using this method. Owing to high accuracy and generalization, it is used in many applications [26]. It is used with small data sets due to stability of predictive model accuracy when compared to several other approaches [27], [28]. A particular class of SVM is SVR.SVR has stability performance in small datasets and a good nonlinear fitting capacity [29]. SVR applies kernel functions to map a non-linear regression into a linear regression problem [30]. Sigmoid kernel function, Radial Basis Function (RBF) kernel function, and the polynomial kernel function are three commonly used kernel functions. Due to fewer variables to be adjusted in Gaussian kernel and its superior prediction performance, it is often used. SVR has been defined elsewhere [31].

Poor selection of model parameters highly affects the general ability of SVR by causing under fitting or over fitting [32]. The C (the trade-off between margin maximization and error minimization), the ε which denotes how much error we are willing to allow per data instance, and the value of γ in RBF should be tuned. There are no wide-ranging rules to choose these parameters [32]. To objectively tune these parameters, the Genetic Algorithm (GA) was employed and compared to particle warm optimization (PSO) in terms of validation in the present work.

B. SKIN-CORE EFFECT

One of the structural flaws which occurs during the process of thermal stabilization is skin-core effect. This defect causes heterogeneity in the structure of stabilized fiber. This defect also reduces the mechanical properties of the fibers [33]. The content of oxygen in the core of the stabilized PAN is less than the content of oxygen in the skin under this defect [34], [35]. This defect should be considered as an objective in the optimization process due to its importance in performance of final fibers [19].

To examine the skin-core structure, the results of [12] was employed. The result was then used for optimization purposes.

To find the probability of the skin-core defect, Golkarnareji et al. [12] used a non-parametric distribution. The obtained model, in their case study, was:

$$SC = \begin{cases} 100 \times \begin{pmatrix} 1.1715\times 10^3 - 9.9233T - 3.8936\times 10^{-2}S \\ -6.5418\times 10^{-2}\sigma + 2.1042\times 10^{-2}T^2 \\ +1.5056\times 10^{-16} exp\,(S) \\ -7.6513\times 10^6\,(T.S.\sigma)^{-2} \end{pmatrix} \\ 0.0001 : SC < 0.0001 \\ 99.9999 : SC > 99.9999 \end{cases} \tag{2}$$

where SC shows the probability of occurrence of skin-core phenomena. The performance criteria, Standard Error of Prediction (SEP) and the coefficient of determination (R^2) were reported to be 0.0856 and 0.9235 respectively.

C. OPTIMIZATION OF STABILIZATION PROCESS

Multiple objectives cannot be optimized concurrently and usually they are often conflicting in engineering problems. In classical optimization problems, a given function with a single objective is optimized by finding a unique solution. In a problem of multi-objective optimization, however, more than one objective function are involved [36]. Multi-objective optimization should often also satisfy several numbers of inequality or equality constraints while giving overall optimal values for the objectives. Multi-objective optimization has been used in many past applications [37]–[41]. Such problems have mainly the following properties:

1) They have various search spaces.
2) There are different goals of optimization.
3) There is more than one optimal set, hence yielding trade-off/ Pareto fronts.

Multi-objective optimization involves a search in an objective space called Z which is multi-dimensional. The complexity of this space represents an important difference between multi-objective and single-objective optimization processes [42].

Two methods are involved in explaining multi-objective optimization problems. In the first method, all the objectives are aggregated into one function, or all but one objective is moved into the sets of constraint sets. Method like utility theory and weighted sum technique are used to deal with the first approach. The problem with this approach is that it is not easy to select the weights and utility functions. In the latter case, the aim is to find a group of Pareto-optimal solutions (optimal solutions) instead of one best solution [36], upon which the final decision can be made by the designer. Mathematically, each Pareto point is an efficient solution of the Multi-Objective Problem (MOP). A MOP can be formulated as follows:

$$F(X) = [f_1(X), f_2(X), \ldots f_m(X)]^T \tag{3}$$

where d is the number of design variables and $X = [x_1, x_2, x_3, \ldots, x_d]$ is the vector of variables. As addressed, one method for converting a MOP into single–optimization problem is to use weight factors. This approach can be written as:

$$F = \sum_{n=1}^{N} w_n f_n \tag{4}$$

where f_n, N and w_n represent objective functions, the number of objective factors, and weighting factors respectively. Equation (3) must be evaluated to find a group of best solutions by using different weight factors, which is very time consuming and also guarantees efficient solutions only if the actual (unknown) search space is convex. As such, the usual way of solving this kind of problems is to save and store a set of Pareto-optimal solutions and update them at each iteration, while assuming convexity. A solution is called a Pareto-optimal solution if the conditions below are satisfied [43]:

Pareto dominance:

$U = (u_1, u_2, u_3, \ldots..u_n) < V = (v_1, v_2, v_3, \ldots..v_n)$ based on the following inequalities:

$$\begin{cases} f_i(u) \le f_i(v) \forall i \\ f_i(u) < f_i(v) \exists i \end{cases} \qquad i = 1, 2, 3_{2\ldots 2}n \tag{5}$$

where n is the number of objective functions.

Pareto frontier Differential Evolution (PDE), Multi-objective genetic algorithm (MOGA), micro genetic algorithm (Micro-GA), strength Pareto evolutionary algorithm (SPEA), and Pareto-archived evolution strategy (PAES) are multi objective optimization techniques.

Among these different methods, MOGA was chosen to create the Pareto front as one of the most fast and prevalent multi objective approaches[44]. Theoretically, individual solutions on Pareto front cannot optimally satisfy all the objectives simultaneously. However, the closest optimum solution to the ideal solution can be chosen by a designer from the Pareto front. This solution would be considered as the best satisfactory result, especially for a conservative designer. One of the effective method to find this final result is the TOPSIS in multiple criteria decision making problems[44]. The TOPSIS process is:

The value of the objectives composes an attribute matrix (Table 2).

As shown in Table 2, P_j (j=1, 2, 3,..., m) are jth individual on the Pareto front, $i = (r_{i1}, r_{i2}, \ldots, r_{im})^T$ (i =1, 2, 3, 4, ...) is the vector of objective function of the ith individual, and m is the number of individuals in the attribute matrix. The decision matrix is then normalized due to the fact that the objectives are not comparable directly due to their differences

TABLE 2. Attribute Matrix.

Individuals	F_1	F_2
P_1	r_{11}	r_{12}
P_2	r_{12}	r_{22}
….	….	….
P_j	r_{1j}	r_{2j}
….	….	….
p_m	r_{1m}	r_{2m}

in magnitudes and units. The normalization method can be:

$$r_{ij} = \frac{F_i^{Max}(p_j) - F_i(p_j)}{F_i^{Max}(p_j) - F_i^{Min}(p_j)} \tag{6}$$

where $F_i^{Max}(p_j)$ and $F_i^{Min}(p_j)$ are the maximum and minimum values in vector F_i and $F_i(p_j) = r_{ij}$.

The $z*$ (ideal solution) and z^{-1} (negative ideal solution) can be estimated based on the set of best and worst values observed under each objective. Using the Euclidean norm, the distance between the ideal solutions and individuals and the negative solution are as follows:

$$F_j^* = \sqrt{\sum_{i=1}^{2}(z_{ij}-1)^2} \quad (j = 1, 2, 3, \ldots, m) \tag{7}$$

$$S_j^- = \sqrt{\sum_{i=1}^{2}(z_{ij}-0)^2} \quad (j = 1, 2, 3, \ldots, m) \tag{8}$$

where z_{ij} is the weighted element in the decision matrix and W_i is the weight coefficient of the ith objective:

$$z_{ij} = W_i r_{ij}^{'} \tag{9}$$

Finally, the relative adjacent degree of each solution has been computed by the distance between the positive and the negative best solution.

$$C_j^* = \frac{S_j^-}{S_j^- + S_j^+} \quad (j = 1, 2, \ldots, m) \tag{10}$$

where $0 \leq C_j^* \leq 1$. The closer the C_j^* is to 1, the closer the individual is to the best solution.

V. RESULTS AND DISCUSSION

To develop models for prediction of density, the tensile strength and Young's modulus of fibers, 23 experimental data were captured and split randomly into 70% training and 30% testing: 16 was chosen for model development based on the L16 of Taguchi method, and 7 to validate the developed models. To reduce experimental tests and obtain the best results, the Taguchi design was modified by adding some marginal operating parameters. To improve the numerical performance of the models, the inputs were normalized between 0 and 1 [44].

In the presence of limited date, the leave-one-out cross-validation technique was carried in SVR algorithm. The method has been run 20 times and the model with the lowest SEP was selected. The support vector regression results were compared to ANN method to develop predictive models for mechanical and physical properties and the result indicated that this method is suitable for the prediction of physical and mechanical properties. Then in order to predict the physical and mechanical properties with highest accuracy, the model parameters were tuned based on a developed GA algorithm and compared to PSO in terms of validation. As the population size is one of the key parameters effecting the obtained solutions, a GA algorithm was developed based on varying different population size. The minimum number of population size was 5 and was incremented by 5 until the least amount of error was obtained. When the population size was around 45, the accuracy stopped improving. Hence, with population size of 45, the accuracy of 99.95 was reached.

A. SVR FOR DENSITY PREDICTION

To predict density, an SVR model was developed based on TTT. Following Xu *et al.* [45], the values for γ, C, and ε were selected. The developed GA was also used to tune C, γ, and ε to obtain the optimum values (Table 3). As stated before, for purpose of training 16 samples were chosen. 7 samples were also selected for the purpose of testing. The Gaussian RBF kernel function [31] was applied for SVR prediction. In addition, SEP, $R^2$and Adjusted R^2 were chosen for checking the accuracy of the model and was calculated to be 0.1260, 0.9989, and 0.9972 respectively. The accuracy of 5% was selected in this study to determine the acceptable level of variation. Fig. 4 illustrates the model and approves that the

TABLE 3. The Optimum Value of SVR Parameters Using GA (Density).

Level	*C*	γ	ε
SVR-GA	14.55	-2.38	0.1030

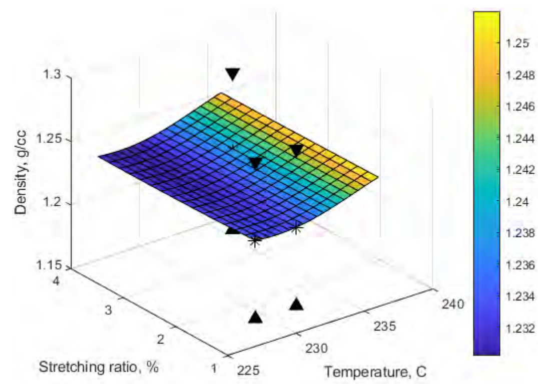


FIGURE 4. Prediction results of SVR model for density; (∗) is the validation experimental data and (▼) and (▲) are upper and lower 5% error limitations (at space velocity of 35 m/s).

TABLE 4. Validation and Comparison of the Prediction Models (Density).

Extra Experiment #		1	2	3	4	5	6	7
Temperature, °C		227	230	230	230	233	233	233
Stretching ration, %		35	20	25	35	20	30	35
Space Velocity, m/h		1	4	3	1	4	3	3
ρ_{actual}, gr/cm^3		1.2339	1.2588	1.2464	1.2335	1.2601	1.2421	1.2372
ANN-LMA	$\rho_{predicted}$	1.2277	1.2688	1.2601	1.2337	1.2623	1.2483	1.2406
	Error, %	-0.5	0.8	1.1	0.0	-0.2	0.5	0.3
SVR-PSO	$\rho_{predicted}$	1.2530	1.2576	1.2531	1.2530	1.2617	1.2440	1.2350
	Error, %	-1.6	-0.1	-0.5	-1.6	0.1	0.2	0.2
SVR-GA	$\rho_{predicted}$, gr/cm^3	1.2337	1.2581	1.2493	1.2359	1.2613	1.2414	1.2353
	Error, %	-0.2	-0.0	0.2	0.0	0.0	-0.0	-0.0

TABLE 5. The Optimum Value of SVR Parameters Using GA (Young's Modulus).

Model	C	γ	ε
SVR-GA	8.2955	1.7028	3.05×10^{-5}

experimental data and the SVR model predicted values are in excellent agreement.

1) PREDICTIVE MODEL VALIDATION

To validate the developed SVR model, the prediction accuracy for seven experimental data were examined. Table 4 shows the validation results of prediction obtained from SVR models and comparison with ANN. The results reveal that the developed model based on SVR is precise and consistent to predict the physical properties. This model was used in the subsequent analysis steps to optimize the energy consumption.

2) SVR FOR MECHANICAL PROPERTIES

To predict the tensile and modulus based on the TTT, SVR models were developed (Figs. 5 and 6). The optimum values of modelling parameters of SVR (Table 5 and 6) were obtained by using the developed GA. Similar as before, 16 samples were used for training and 7 were chosen for validation. The Gaussian RBF was reselected and applied as kernel function in SVR model. Furthermore, SEP, R^2, Adjusted R^2were chosen for model performance. Table 7 and Table 8 illustrate the of the developed models performance for the Young's modulus and tensile strength properties. All the predicted values were within the 5% error range. All the images are at space velocity of 35 m/s.

Fig. 5 and Fig. 6 confirm that the experiments and the obtained predictions based on SVR model are in good agreement.

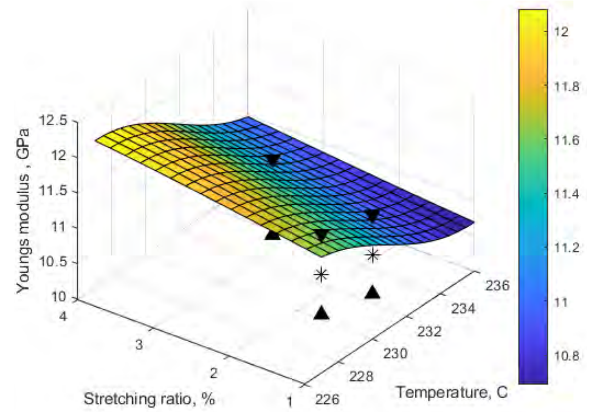


FIGURE 5. Prediction results of Young modulus model; (∗) is the validation experimental data and (▼) and (▲) are upper and lower 5% error limitations.

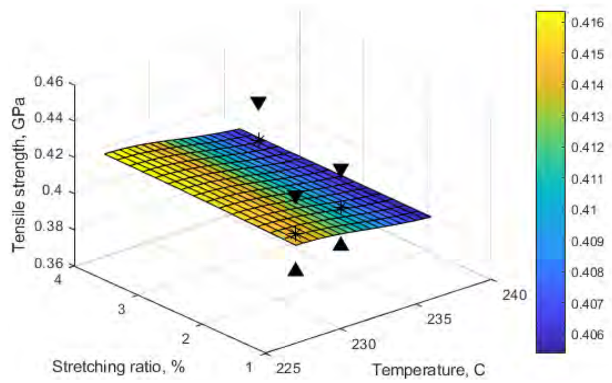


FIGURE 6. Prediction results of Tensile strength model; (∗) is the validation experimental data and (▼) and (▲) are upper and lower 5% error limitations.

TABLE 6. The Optimum Value of SVR Parameters Using GA (Tensile Strength).

Model	C	γ	ε
SVR-GA	5.3270	-1.8698	3.05×10^{-5}

TABLE 7. Performance Criterion of SVR Model for Young's Modulus.

Model	R^2	Adj_R^2	SEP-testing
SVR-GA	0.9987	0.9985	0.2490

B. PREDICTIVE MODEL VALIDATION

For the purpose of validation, 7 extra points were selected, Table 9 and Table 10 show the validation of SVR models. The results show that SVR-GA model is precise and consistent to predict Young's modulus and tensile strength of OPF. The result obtained from developed SVR model has been compared with that of ANN and integrated SVR and PSO [25]. The result indicated that SVR-GA model is the best developed model to be used in terms of predicting the physical and mechanical properties [25]. The results were used as a constraint to optimize the stabilization process.

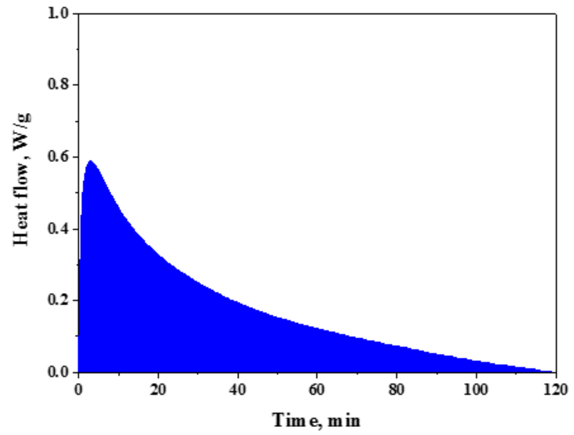


FIGURE 7. Isotherm DSC results at 227° C for PAN precursor after normalization and baseline adjustment. The area under curve presents the heat of thermal stabilization reaction set.

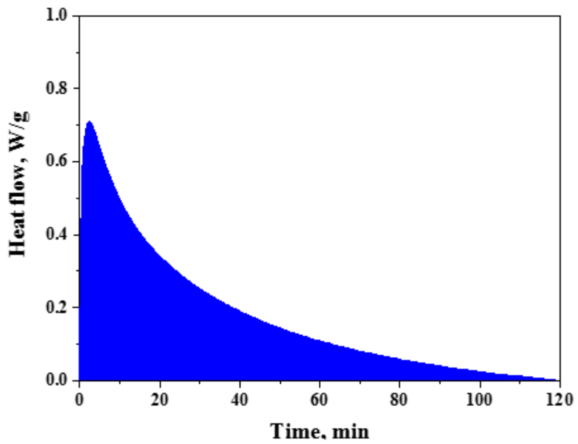


FIGURE 8. Isotherm DSC results at 233° C for PAN precursor after normalization and baseline adjustment. The area under curve presents the heat of thermal stabilization reaction set.

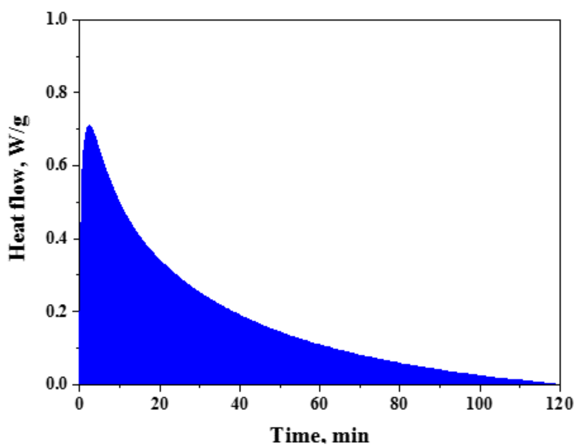


FIGURE 9. Isotherm DSC results at 233° C for PAN precursor after normalization and baseline adjustment. The area under curve presents the heat of thermal stabilization reaction set.

C. ENERGY SOURCES AND MODEL STRUCTURE

Recycling and exhaust fans, air electrical heater, drives 1 and 2, and tow of PAN fiber are sources of energy consumption. The Energy is released during the thermal stabilization process. To avoid the likelihood of combustion, due to fast release of energy, it is managed by using cold ‘‘makeup’’ air which controls the temperature inside the oven. Differential Scanning Calorimetry (DSC) on the PAN precursor was used to scrutinize the amount of released energy during the thermal stabilization process or heat of set of thermal stabilization reaction. In order to find the heat of reaction, four different isothermal DSC tests were designed using temperature levels (227, 230, 233, and 236 °C) mentioned in section 2.1. Fig. 7 to Fig. 10 show the results of DSC test for each of these temperature levels after normalization and baseline adjustment. The area under each curve represents the heat of set of thermal stabilization reaction or released energy during the process for 1g of PAN precursor.

Fig. 11 shows the amount of heat of reaction versus stabilization temperature based on 120min of DSC test. The results

TABLE 8. Performance Criterion of SVR Model for Tensile Strength.

Model	R^2	Adj_R^2	SEP-testing
SVR-GA	0.9980	0.9838	0.0143

TABLE 9. Validation and Comparison of Prediction Model (Young's Modulus).

Test #		1	2	3	4	5	6	7
Temperature , °C		227	230	230	230	233	233	233
Stretching ration, %		35	20	25	35	20	30	35
Space Velocity, m/h		1	4	3	1	4	3	3
Y_{actual}, GPa		11.1551	11.4838	10.8232	11.0284	10.8440	10.7525	10.7225
ANN-	$Y_{predicted}$	11.573	11.3751	10.6399	10.6342	10.9432	10.6444	10.4028
	Error, %	-3.75	0.95	1.7	3.57	-0.92	1.01	2.98
SVR-PSO	$Y_{predicted}$	11.1204	10.9315	10.9864	10.4887	11.0359	10.8052	10.6506
	Error, %	0.31	4.8	1.51	4.9	-1.8	-0.5	0.7
SVR-GA	$Y_{predicted}$, GPa	11.6741	11.1995	10.7224	11.2941	10.8786	10.9710	10.7387
	Error, %	4.7	-2.5	0.9	2.4	0.3	2.	0.1

TABLE 10. Validation and Comparison of Prediction Model (Tensile Strength).

Test #		1	2	3	4	5	6	7
Temperature, °C		227	230	230	230	233	233	233
Stretching ration, %		35	20	25	35	20	30	35
Space Velocity, m/h		1	4	3	1	4	3	3
T_{actual}, GPa		0.4210	0.3945	0.3953	0.3985	0.3987	0.4108	0.4100
ANN-LMA	$T_{predicted}$	0.4202	0.3958	0.3796	0.4139	0.3867	0.4168	0.4424
	Error, %	0.2	-0.3	4.6	3.1	1.2	-4.8	-4.4
SVR-PSO	$T_{predicted}$, GPa	0.4206	0.3952	0.4024	0.4095	0.3852	0.3997	0.4304
	Error, %	-0.1	0.2	1.8	2.8	-3.4	-2.7	5.0
SVR-GA	$T_{predicted}$, GPa	0.4138	0.3904	0.3999	0.4074	0.3984	0.4313	0.4238
	Error, %	-1.7	-1.0	1.2	2.2	-0.1	5.0	3.4

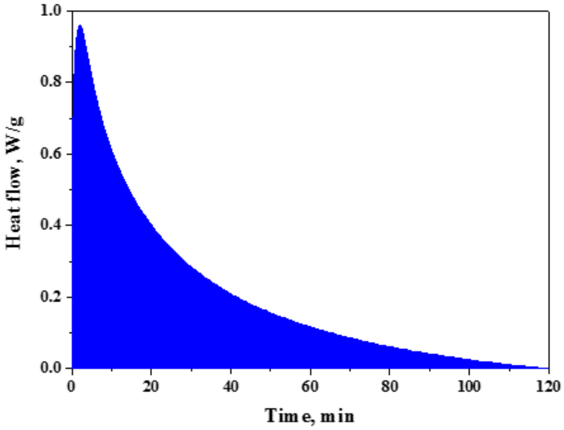


FIGURE 10. Isotherm DSC results at 236° C for PAN precursor after normalization and baseline adjustment. The area under curve presents the heat of thermal stabilization reaction set.

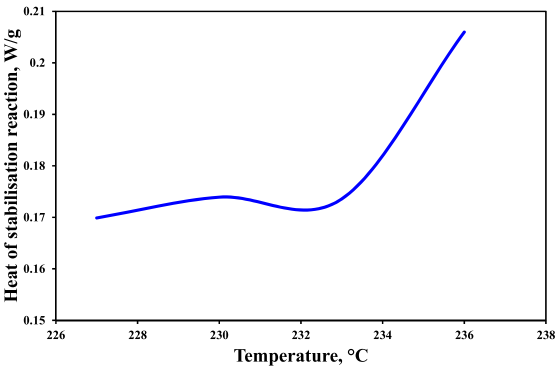


FIGURE 11. Heat of stabilization reaction (W/g fiber) vs temperature of oven.

illustrate that the heat of reaction is almost constant at around 0.17 W/g until 233° C. This, however, increases around 0.032 W/g at the temperature of 236° C. This presents the change in the mechanism of chemical reactions at above 233° C. Although, drawing any conclusions from these results requires more advanced experiments, the magnitude of the heat of reaction would be negligible when compared to the total power of the heater (32000W), particularly with respect to fresh "makeup" air for adjusting the temperature inside the oven. A simple calculation shows when the tow speed is 35 m/h (the worst case), the amount of released power is 4.5709 W (refer to Equations (11 a to d)); therefore, the effect is not substantial on the overall consumption in stabilization process and can be disregarded.

$$\rho_L = 1.5411\ dtax \tag{11a}$$

$$\begin{aligned} m &= Mass\ of\ 6m\ Tow\ (24000\ filaments) \\ &= 24000 \times 6 \times \frac{1.5411}{10000} = 22.1917 \end{aligned} \tag{11b}$$

$$\Delta H_{236^\circ\mathrm{C}} = 0.2060 {}^{W}\!/_{g} \tag{11c}$$

$$\begin{aligned} Released\ power &= \Delta H_{236^\circ} m = 0.2060 \\ &\quad \times 22.1917 = 4.5709W \end{aligned} \tag{11d}$$

As the system is almost isothermal, the oven temperature was assumed to be homogeneous, especially in the center of the oven.

The energy consumption of the currents of exhaust fan, recycling fan, drive 1, and drive2 resources, was estimated using (12) [46].

$$P = \sqrt{3}.V.I.\,|\cos\varphi| \tag{12}$$

where P is power (W), V is voltage (450 volts), I is current (A), and φ is the phase difference (120°). The SVR method predicted the relationship between the rise in the temperature and the power that the heating system consumes. Based on [46], the developed model for energy consumption was:

$$\begin{aligned} \sigma E\,(T, S,) = &\frac{3600 \times L.\,(P_{Oven})}{S} \\ &+ \frac{\sqrt{3} \times 3600 \times V_{F_1}.I_{F_1}.L.\,|\cos\varphi|}{S} \\ &+ \frac{\sqrt{3} \times 3600 \times V_{F_2}.I_{F_2}.L.\,|\cos\varphi|}{S} \\ &+ \frac{\sqrt{3} \times 3600 \times V_D.I_D.L.\,|\cos\varphi|}{S} \end{aligned} \tag{13}$$

where T, S, σ, E, P_{Oven} and L are temperature (° C), space velocity (m/h), stretching ratio (%), the amount of energy consumption (for 6m fibers in joules), power of electrical heater and tow length ($L = 3\ \times$2m). The voltage and current of recycle fan, exhaust fan and drives are shown as $V_{F_1}, I_{F_1} V_{F_2}, I_{F_2}$, and $V_{D,} I_D$.

VI. MULTI-OBJECTIVE OPTIMIZATION OF ENERGY CONSUMPTION AND SKIN CORE DEFECT

As noted earlier, more than one objective is optimized at the same time in multi-objective optimization problems. The objectives in multi-objective optimization problems may or may not conflict each other, but mostly they are conflicting in practice. In these problems, multiple optimal solutions exist, and the best among them is chosen, based on the priorities of the designer. Due to industrial request and preferences of the manufacturer, both skin-core defect and energy consumption were considered equally important and as the objective functions in the problem of optimization:

$$\begin{aligned} &Minimize\ : E\,(T, S, \sigma) \\ &Minimize\ : Skin - core\ area\% \end{aligned}$$

$$Subject\ to: \begin{cases} S_{min} \le S \le S_{max} \\ T_{min} \le T \le T_{\max} \\ \sigma_{min} \le \sigma \le \sigma_{max} \\ \rho \approx SVR\ model\ developed\ for\ \rho \\ TS \approx SVR\ model\ for\ TS \\ YM \approx SVR\ model\ for\ YM \end{cases}$$

where Skin-core area% is the probability of skin-core defect to be minimized, E is the energy consumption, ρ is density, YM is Young's modulus and TS is tensile strength.

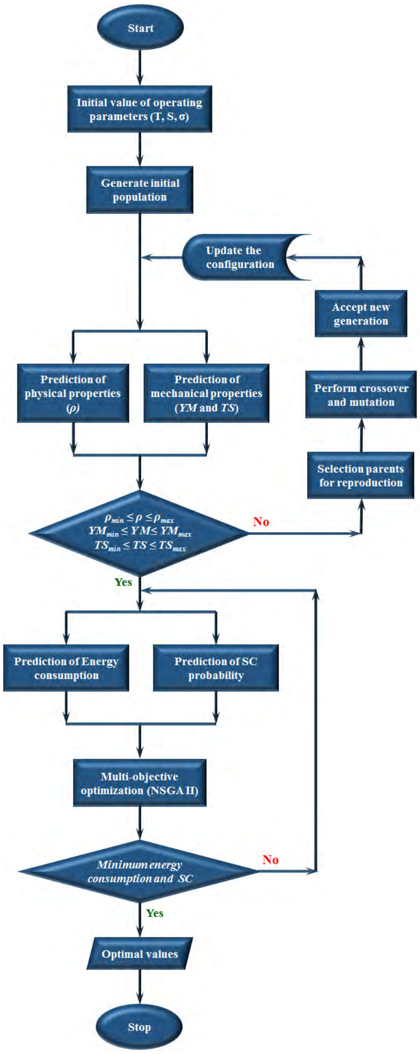


FIGURE 12. The SVR-NSGA_II-TOPSIS algorithm used for energy optimization procedure.

TABLE 11. Feasible Solutions for Operational Parameters (T, S and σ): (1) 1.23g/cm^3 $\le \rho \le$ 1.25 g/cm^3, (2) 11 GPa $\le$ YM $\le$ 12.5GPa, and (3) 0.4 GPa $\le$ TS $\le$ 0.5GPa Using NSGA-II.

#	Temp., °C	Sp. Vel., m/h	Str. Rat., %	Skin-core, %	Energy, J
1	227.0347	34.9999	1.6563	0.2932	4366028.7
2	227.0479	34.9204	1.8843	0.2279	4376758.0
3	227.0303	34.6017	1.9690	0.0564	4416004.9
4	227.0207	34.4468	1.9974	0	4435292.7
5	227.0354	34.9320	1.9050	0.2407	4374564.9
6	227.0250	34.5050	1.7947	0.0296	4428064.0
7	227.0347	34.9999	1.6563	0.2932	4366028.7
8	227.0363	34.7120	1.7976	0.1147	4402336.3
9	227.0241	34.7599	1.97815	0.1354	4395544.3
10	227.0328	34.6569	1.8461	0.0864	4409123.6
11	227.0424	34.5091	1.9327	0.0260	4428593.5
12	227.0210	34.5647	1.9696	0.0419	4420182.8
13	227.0353	34.7785	1.9201	0.1446	4393862.1
14	227.0358	34.94032	1.8036	0.2510	4373539.9
15	227.0337	34.6926	1.8699	0.1019	4404642.8
16	227.0267	34.6648	1.9086	0.0879	4407758.5
17	227.0267	34.6249	1.9833	0.0657	4412830.4
18	227.0208	34.4847	1.9839	0.0125	4430421.2
19	227.0436	34.9009	1.9325	0.2152	4378944.0
20	227.0308	34.8311	1.8919	0.1798	4386954.5
21	227.0435	34.8821	1.9259	0.2036	4381295.8
22	227.0348	34.9883	1.8714	0.2759	4367492.5
23	227.0269	34.8230	1.9942	0.1714	4387739.9

TABLE 12. Feasible Solutions for Operational Parameters (T, S and σ): (1) 1.25 g/cm^3 $\le \rho \le$ 1.26 g/cm^3, (2) 10GPa $\le$ YM $\le$ 12GPa, and (3) 0.35GPa $\le$ TS $\le$ 0.45 GPa Using NSGA-II.

Solutions	Temper., °C	Space-velocity, m/h	Stretching Ratio, %	Skin-core defect, %	Energy consump, J
1	227.1876	26.5824	3.9629	0	5760077.5
2	232.9852	27.1343	3.9510	1	5732894.0

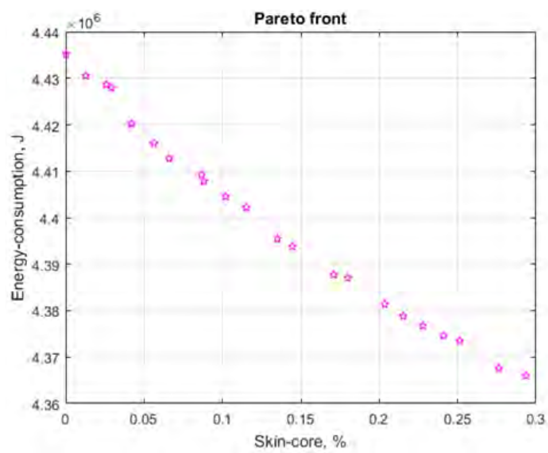


FIGURE 13. Feasible solutions for operational parameters (T, S and σ) and the corresponding energy consumption and skin-core percentage with density 1.23 g/cm^3 $\le \rho \le$ 1.25 g/cm^3.

To address this MOP problem, NSGA-II optimization was used [47]. Population size = 45, mutation probability = 0.2, generation size = 600, and crossover probability = 0.8 are the parameters of NSGA-II. Fig. 12 shows the procedure of the energy optimization. In this MOP problem, energy consumption and skin-core defect are minimized based on SVR models developed individually for density, tensile strength and Young's modulus. Space velocity, temperature and stretching ratio was also added as constraints. Because NSGA-II is a stochastic heuristic algorithm, 30-independent-runs with different initial parameters have been carried out to obtain a realistic Pareto front as shown in Fig. 13.

The elapsed time was 924.211 seconds. Several solutions were achieved, and the corresponding operational parameters of these solutions are listed in Table 11 and Table 12. Fig. 13 and Fig. 14 illustrate the feasible optimized solutions for energy consumption and the skin-core defect. The vertical axis in these figures denotes the energy consumption, while the horizontal axis represents the skin-core defect in percentages.

As it can be seen in Table 11 and Fig. 13, the optimization solution is not unique. All these points are optimal solutions and non-superior to others and can be chosen as a feasible

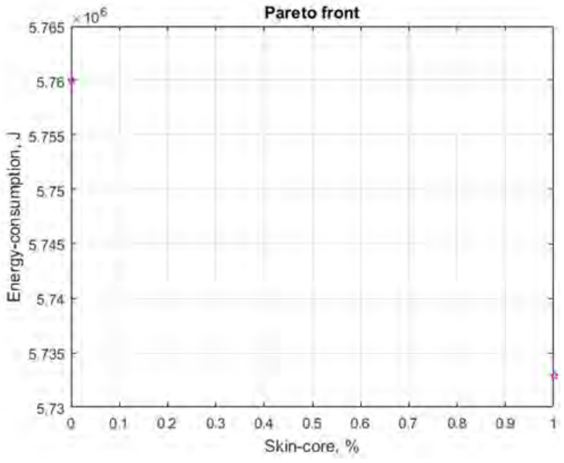


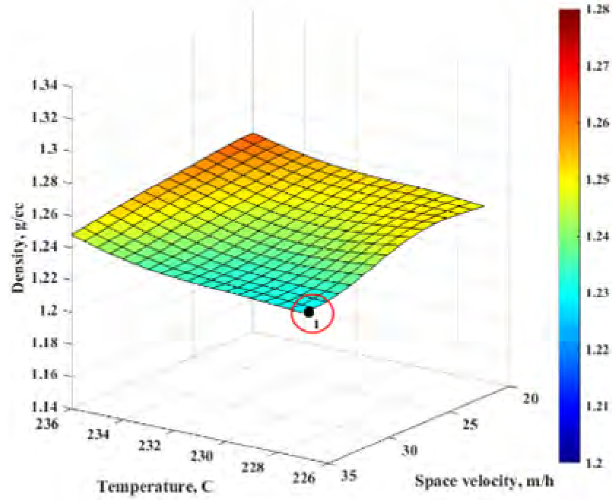
FIGURE 14. Feasible solutions for operational parameters (T, S and σ) and the corresponding energy consumption and skin-core percentage with density 1.25 g/cm^3 $\leq \rho \leq$ 1.26 g/cm^3.

TABLE 13. Closeness Coefficient of Feasible Solutions.

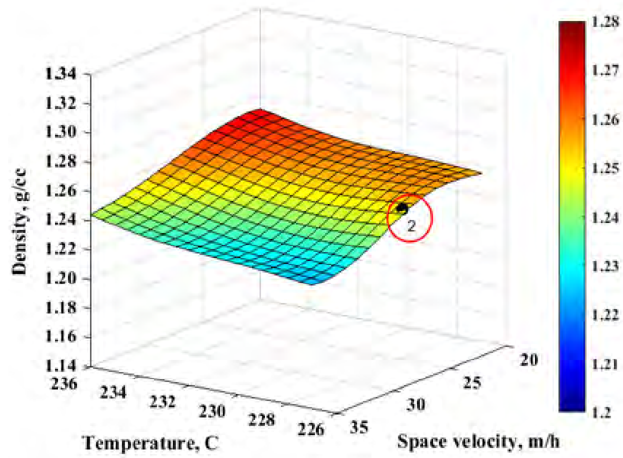
Solutions	Relative adjacent degree (closeness coefficient)
1	4.53×10^{-7}
2	0.2227
3	0.8076
4	0.9999
5	0.1791
6	0.8990
7	4.53×10^{-7}
8	0.6088
9	0.5382
10	0.7053
11	0.9113
12	0.8571
13	0.5068
14	0.1439
15	0.6525
16	0.7002
17	0.7759
18	0.9574
19	0.2660
20	0.3868
21	0.3056
22	0.0590
23	0.4154

solution. The final solution must be selected based on engineering requirements.

In our case, the two values of the objective functions formed the decision matrix for TOPSIS. The dimension of this matrix was (23, 2). The objectives were considered equally important, w = (1, 1). Based on the decision matrix, solution 4 was chosen as the final solution according to Table 13. Similarly, for the case when the density constraint was 1.25 g/cm^3 $\leq \rho \leq$ 1.26 g/cm^3 the solution with skin core ≈ 0 was selected. Table 14 and Fig. 15(a and b) show the optimized operational parameters and the position of the optimized energy criterion, respectively.



(a)



(b)

FIGURE 15. Position of the optimized energy criterion based on different density Young's modulus and Tensile strength constrains: (a) 1.23 g/cm^3 $\leq \rho \leq$ 1.25 g/cm^3, (b) 1.25 g/cm^3 $\leq \rho \leq$ 1.26 g/cm^3 with 11 GPa $\leq$ YM$\leq$ 12 GPa, 0.4 GPa $\leq$ TS $\leq$ 0.5 GPa and zero skin-core defect.

The results show the advantage the multi-objective optimization algorithm, with an energy saving of up to 44.62 in thermal stabilization process with the density constraint of 1.23 $\leq \rho \leq$ 1.25 g/cm^3. The results were also compared with NSGA III which is a reference-point-based multi objective algorithm. Almost similar results were obtained with temperature, space velocity, and stretching ratio to be 227.0323, 34.1642, 1.9962.

In addition, in another study, by considering only energy consumption as an objective function, the energy saving was up to 42.7% with the density constraint of 1.23 $\leq \rho \leq$ 1.25 g/cm^3 [25] compared to 44.62% in multi-objective optimization with similar situation. The outcome illustrates the benefit of the multi-objective optimization method compared with the single-objective optimization method in optimizing consumption of energy in thermal stabilization process.

TABLE 14. Optimized operational parameters (T, S and σ): (1) 1.25 g/cm^3 $\leq \rho \leq$ 1.2 g/cm^3, (2) 11 GPa $\leq$ YM $\leq$ 12.5 GPa, and (3) 0.4 GPa$\leq$ TS $\leq$0.5 GPa using NSGA-II.

no.	Density constraint, g/cm^3	Skin-core area, %	T, °C	S, m/h	σ, %	Predicted density, g/cm^3	Actual density, g/cm^3	Predicted modulus, GPa	Actual modulus, GPa	Predicted tensile stren., GPa	Actual tensile stren., GPa	Opt. energy consump., MJ	Max. energy consump., MJ	Density error. %	Tensile error%	Modulus error %	Energy saving, %
1	$1.23 \leq \rho \leq 1.25$	0	227.0	34. 5	2.0	1.229	1.2339	11.712	11.1551	0.4203	0.4209	4. 43529	8.010	0.4	4.99	-0.20	44.62
2	$1.25 \leq \rho \leq 1.26$	0	227.1876	26.5824	3.9629	1.2500	1.2417	11.675	12.0780	0.4194	0.4359	5.7600	8.010	0.7	-3.79	-3.3366	28.0898

VII. CONCLUSION

To realize the goal of energy saving while improving the production quality, the multi-objective optimization of thermal stabilization process of PAN fibers is deemed imperative. The main points of this research work can be summarized as;

- Set of predictive models were developed for mechanical and physical properties of the fibers using the SVR method.
- Both skin-core defect and energy consumption were considered as the main objectives in the multi-objective problem.
- NSGA-II has been used to find the optimum Pareto non-dominated solutions between selected conflicting objective functions of the process.
- The best solution was achieved with energy saving of up to 44.62% with a minimal fiber defect probability, while satisfying the design constraints assigned for mechanical and physical properties.

Potential Future work may include using other multi-objective methods including SPEA2, MOPSO, and PAES in this complex system and performing a comparative study.

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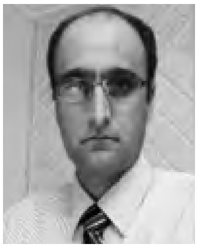

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