



Data-Driven Radial Basis Function Approach to Evaluate the Effect of Process Variables on Solar-Assisted Degradation of Starch-Plastics Composite in an Extruder Reactor

May Ali Alsaffar,^{a,*} Mohamed A. Abdel Ghany^b, Alyaa K. Mageed^c

^{a,b,c} Department of Chemical Engineering, University of Technology-Iraq



Abstract

This study investigated the effect of process variables on the biodegradation of starch-plastics composite. The extrusion process was carried out with low-density polyethylene (LDPE)-starch blends in varied extrusion temperature and extruder speed and starch content. The parametric analysis based on the three-dimensional plots revealed a non-linear relationship between the input parameters and output. The datasets obtained from the extrusion process was employed for data-driven modeling using radial basis function, a machine learning algorithm. The radial basis function was trained using the backpropagation rule resulting in the prediction of the tensile strength, elongation to break, and yield point of the LDPE-starch composite. The robustness of the radial basis function in modeling the process is evident from the R^2 of 0.804, 0.855, and 0.766 obtained to predict tensile strength, elongation to break, and yield point, respectively, with minima prediction errors. The extrusion temperature, extruder speed, and starch content significantly influenced the predicted tensile strength, elongation to break, and yield point. However, the extrusion temperature was found to have the most significant effect. This study can be employed in understanding the appropriate conditions of parameters required to obtain a degradable material based on its mechanical properties.

Keywords: Radial Basis Function; Microplastics; Plastic extrusion; Environmental pollution; extrusion temperature

1. Introduction

The pace of plastic deposition has risen steeply in the past two decades due to wide applications in every facet of life. As a result, huge amounts of plastic have found their ways into the marine ecosystem [1,2]. Several floating plastics found in water bodies globally have serious endangered marine lives and have become one of the most prevalent and persistent contaminants of seas and beaches across the world [1,3]. Environmental contamination from plastic trash was regarded as a cosmetic issue a few years ago. The plastics dispersed in the wind and polluted huge land and water areas [4].

On the other hand, plastic trash undergoes photo-oxidation when exposed to ultraviolet radiation from sunshine [5]. Because of this degradation, the plastic begins to break down and crumble into microplastic particles [6,7]. As a result of the menace of plastic pollution, several nations have banned the usage or production of plastic bags [8,9]. Nevertheless, it has been found that several of the fast-developing countries still dump huge quantities of plastic into the oceans [10]. Plastics are not easily degradable due to

their persistent nature, and they can have major negative effects on the environment and human health [11].

Several measures such as proper disposal and collection of plastic waste, recycling, valorization of waste plastics, landfilling, and biodegradation have been investigated [12]. Amongst these strategies, biodegradation of the plastic wastes has been reported to be very effective in mitigating the effect of waste plastic on the environment [13,14]. To help facilitate the degradation of plastics, chemical additives and polymers are mixed with plastics [15]. When exposed to sunlight, the additives and polymers help break down plastic by composting or photochemical degradation [16]. During biodegradation, the effects of natural microorganisms such as bacteria, fungi or algae may require conditions such as temperature and other factors. These factors are not often present under ambient conditions to effectively degradation the plastic to water, carbon dioxide and organic matter (mineralization) [17]. The blending of various materials is a cheaper and more cost-effective to

*Corresponding author e-mail: mayrashid1973@gmail.com

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produce polymers degradable with desired properties. Compared to co-polymerization, this process is simpler, quicker, and cheap [18]. The time of breakdown of the polymer mixtures is regulated by a degradable ingredient. Polymer blends are regarded more helpful than fossil-based degradable polymers for some applications because of their financial advantage [19]. There are many types of degradable polymer blends based on starch such as mixtures between starch/polyester and starch/ polyvinyl alcohol (PVA) [19,20]. As a result of the full disintegration of each element in the plastic, they are considered entirely degradable [21]. The primary breakdown process expands the surface area for enzyme activity collapses polymer's structural integrity [22]. Research on the microbial processes of the breakdown of polymer mixtures and different degradation products has increased, as indicated by the extensive review of Koh et al. (2018). Studies have shown that starch and PVA combinations were fully degradable since different microorganisms assimilate [24]. Several authors have thoroughly investigated the processing properties of starch and PVA mixtures [23].

The effect of natural variables on the biodegradation of cassava starch and cornstarch-based simple and composite bioplastics has been reported by Zoungranan et al. [25]. As indicated by the authors, the inclusion of the natural component *Cola cordifolia* improves the biodegradability of composite bioplastics substantially compared to simple bioplastics. Variability in environmental parameters, on the other hand, can benefit or harm biodegradability. The humidity of the soil was observed to enhance the biodegradability of bioplastics, particularly composite bioplastics, to a maximum of 15%. Enrichment in microorganisms is unfavourable over 10% enrichment for simple corn bioplastics and 20% enrichment for composite and simple cassava-based bioplastics. Burial temperatures over 30 °C reduce the biodegradability of bioplastics. In a similar study, the use of oxo-prodegradants and thermoplastic starch-based additives to promote polymer waste biodegradation has been reported by Al-Salem et al. [26]. The study revealed that, after extensive testing and monitoring, it was discovered that the linear low-density polyethylene and the oxo-prodegradant generated polymer waste had a comparable degradation extent of 23% after 180 days of experimentation. Furthermore, after around 50 days, the biodegradation as a function of time achieved a plateau, indicating that the additives in the samples operate as a source of nutrition to support the biodegradation by feeding the soil microorganisms to create carbon. The study leads to a new approach for handling polymer waste that uses physical mixing with additives to biodegrade it over time as a viable

option for plastic trash build-up. Camacho-Muñoz et al. [27] investigated the biodegradation of poly (lactic acid)/starch blend compatibilized by maleic anhydride under anaerobic slurry thermophilic conditions. The authors observed a slow degradation of the polylactic acid which can be ascribed to the elevated glass transition temperature and crystallinity. The results indicate that the polylactic acid-based polymers may not be degradable in very short retention periods. Tai et al. [21] investigated the physical structure and chemical composition changes of aerobic biodegradation of starch–flexible polyurethane films under soil burial conditions. The study revealed that the starch degradation happened first in films made from physically mixed starch–polyurethane, followed by degradation of polyester soft segments of starch–polyurethane. The covalently linked structure was reported to be responsible for the delayed breakdown of films made from chemically grafted starch–polyurethane hybrids. The authors established that the films made from the physically blended starch-polyurethane hybrid materials have the potential to be degradable flexible. Although there are several studies on the blending of starch with plastics to improve its biodegradability, however, there is a dearth of studies on the data-driven approach to study the effect of various parameters on biodegradation of starch-plastics composite. This study therefore employs radial basis function data-driven modeling approach to examine the effect of parameters such as starch content, extrusion speed, extrusion temperature on the mechanical properties of the starch-plastic blend prior to degradation.

2. Experimentation and Model Development

As reported by Vieyra Ruiz et al. [28], the extrusion processing of the LDPE-starch composite was performed by injecting the mixture into a single mould cavity with a volume capacity of 250 mL. The temperature of the extrusion process was set at 150°C. The mechanical properties of the tensile strength, elongation to break, and yield point were determined using a texture analyzer as described by Vieyra Ruiz et al. [28]. The datasets employed for the modeling was generated using various combinations obtained from experimental design of 20 runs with 5 repetitions at the central point. The input parameters include starch content, extrusion temperature, and extrusion speed. The output parameters comprised the tensile strength, the elongation to break, and the yield point of the LDPE-starch composite.

Radial basis function configuration shown in Figure 1 was employed for modeling the effect of parameters such as starch content, extrusion speed, extrusion temperature on the mechanical properties of the starch-plastic blend prior to degradation. The radial

basis function network consists of three nodes namely starch content, extrusion speed, extrusion temperature, ten hidden units, and three targeted outputs namely tensile strength, the elongation to break and the yield point [29–31]. The input nodes are inter-connected with the hidden layers through artificial neurons. Each of the neurons has an associated weight. Softmax and identity activation function were employed at the hidden and output layer, respectively. The performance of the radial basis function was examined using the coefficient of determination (R^2), sum of the square error function and the residual analysis that examined the differences between the observed and the predicted values.

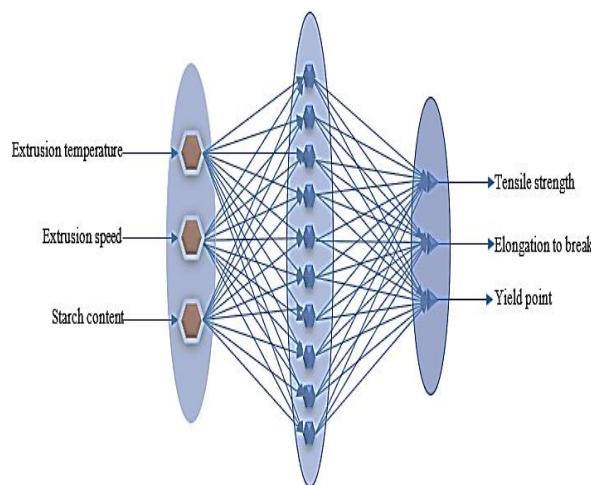


Figure 1: The configuration of the radial basis function network used for the modeling process

3. Results and Discussion

The performance of the radial basis function in terms of the error analysis during training and testing is depicted in Table 1. In configuring the model, it was ensured that overfitting which is a situation where the random error is explained by the model instead of the relationship between the variables is avoided to enhance the generalization of the model outside the original dataset. The dataset was split into two portions to prevent overfitting with 70% used for training and 30% used for testing. The analysis of the model shows that the training and testing of the radial basis function resulted in minima errors as indicated by the sum of squared error (SSE) and R^2 . SSE values of 1.298, 0.273, 5.374 were obtained for the training of the radial basis function used for modeling the prediction of the tensile strength, elongation to break and yield point, respectively. The testing of the models also resulted into SSE values of 0.118, 1.271, and 5.327, for the prediction of the tensile strength, elongation to break and yield point, respectively. This implies the radial basis function network model is robust in modeling the process. This is consistent with that reported by Li et al. [32] for predicting the short-term subway passenger flow under special events scenarios. The performance of the radial basis function network in prediction of the tensile strength, elongation to break and yield point are depicted in Figures 2-4. In Figure 2 (a), It can be seen that the radial basis function network is able to learn the non-linear relationship between the starch content, extrusion speed, extrusion temperature and tensile strength.

Table 1: Summary of the training and testing performance of the radial basis function

	Tensile strength		Elongation to break		Yield point	
	Training	Testing	Training	Testing	Training	Testing
SSE	1.298	0.118	0.273	1.271	5.376	5.328
RE	0.2	0.748	0.045	0.566	0.977	2.548
R^2	0.804		0.855		0.766	

For each experimental point, the observed and the predicted tensile strength are strongly correlated. The highest observed and predicted tensile strength could be identified at experimental point 4, which entails the utilization of 10.1% starch content at an extruder temperature of 153.9 °C and extrusion speed of 32 rpm. In contrast, the lowest observed and predicted tensile strength can be identified at experimental point 18, which is 39.9% starch content, at extruder temperature of 153.9 °C and extrusion speed of 32

rpm. This implies that starch contents significantly influence the tensile strength, which invariably affects the biodegradation of the starch-plastics composite. The residual analysis is shown in Figure 2 (b) show that the residuals which are the differences between the predicted and the observed tensile strength, are within the range of ± 0.53 . The tensile strength prediction resulted in R^2 of 0.804, implying that the radial basis function model can explain over 80% of the dataset. The results obtained in this study is consistent with that reported for Roshani et al. [33]

who employed radial basis function for modeling gas-oil-water three-phase flow regime and determination of volume fraction. A R^2 of 0.874 was obtained for the prediction of volume fraction. Also, the robustness of using the radial basis function agrees with that reported by Chen et al. [34] and Karkevandi-Talkhooncheha and Rostami [35] for modelling the prediction of interfacial energies related to membrane fouling in a membrane bioreactor and minimum miscibility pressure during pure and impure CO_2 Flooding, respectively.

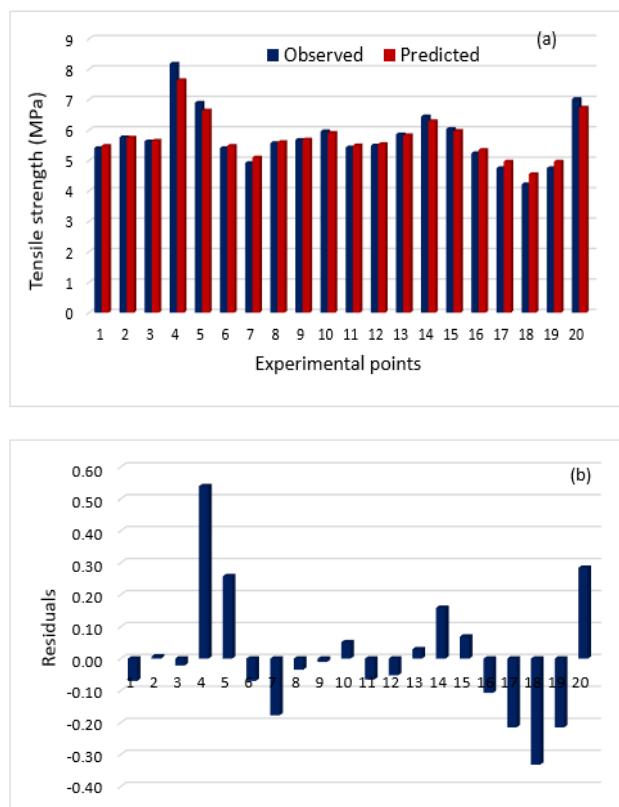


Figure 2: (a) Observed and Predicted tensile strength by the radial basis function (b) residual analysis of the prediction

The performance of the radial basis function network in predicting the elongation of break based on the starch content, extruder temperature and extruder speed is depicted in Figure 3. The predicted and observed elongation to break are closely related for all the experimental datapoints. This is evidence from the R^2 of 0.855 obtained for the predicted elongation to break. This implies that over 85.5% of the datasets can be explained by the radial basis function and generalized for the prediction of the elongation to break. The highest elongation to break the starch-LDPE composite can be identified at experimental

point 2, which utilizes starch content of 10.1%, extruder temperature of 136.1°C and extruder speed of 32 rpm. The lowest elongation to break the starch-LDPE composite can be identified at experimental point 18, which utilized 39.9% starch content, 153.9 °C extruder temperature, and 32 rpm extruder speed. It can be seen that both starch content and the extruder temperature significantly influence the elongation to break of the starch-LDPE composite, which will invariably influence the biodegradation of the starch-plastics composite. The residual analysis is shown in Figure 3 (b) revealed that the elongation to break the starch-LDPE composite is ± 1.40 . An error function of 7.048 based on the RMSE was reported by Zhu et al. [36] to predict traffic volume with the consideration of traffic flows at the adjacent intersections. The study revealed that the radial basis function was robust in classifying mammograms based on Gray-level Co-occurrence Matrix texture-based features.

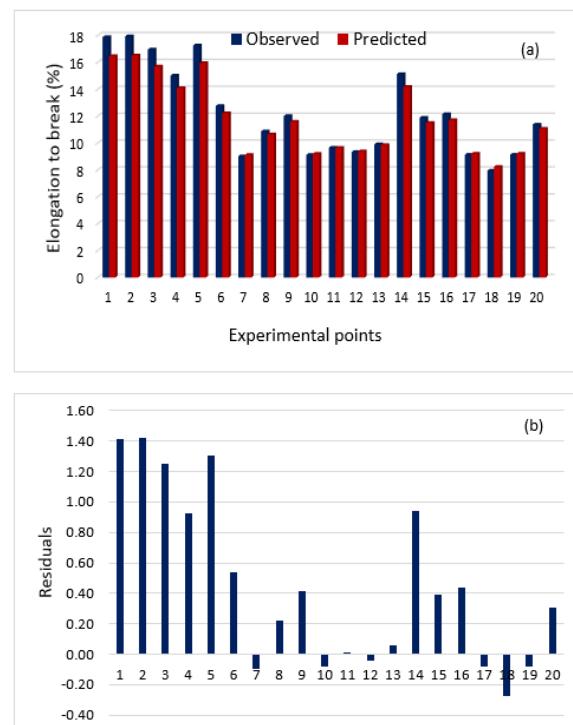


Figure 3: (a) Observed and Predicted elongation to break by the radial basis function (b) residual analysis of the prediction

The performance of the radial basis function used for modeling the non-linear relationship between the starch content, extruder temperature, extruder speed and the yield point of the starch-LDPE composite is depicted in Figure 4. As shown in Figure 4 (a), the observed and the predicted yield points obtained for each experimental point are closely related. The highest yield point of the starch-LDPE composite can be identified at experimental

points 14, which utilized 25% starch content at an extrusion temperature of 145 °C and extruder speed of 60 rpm. Whereas experimental point 18 with 39.9% starch content, 153.9 °C extrusion temperature, and 32 rpm extruder speed yielded the smallest observed and expected yield. It can be seen that a lower starch content, temperature and higher speed promote a higher yield point which could have a significant effect on the biodegradation of the starch-LDPE composite. The R^2 of 0.766 obtained for predicting the yield point shows that over 76% of the datasets can explain the non-linear relationship between the starch content, extruder temperature, extruder speed and the yield point. The residual analysis obtained from the prediction of the yield points by the radial basis function is depicted in Figure 4 (b). The residuals of the prediction are within the range of -1.4 to 0.52. The robustness of the radial basis function in modeling the prediction of solubility of N-alkanes in supercritical CO₂ has been reported by Abdi-Khanghah et al. [37] with a prediction of 0.136 based on the root mean squared error.

The interaction effect of extrusion speed and extrusion temperature on the tensile strength, extrusion speed and extrusion temperature on the elongation to break, extrusion speed and extrusion temperature on the yield point as well as the level of importance analysis of the input parameters to the radial basis function are depicted in Figure 5. As shown in Figure 5 (a)-(c), there is a non-linear relationship between the tensile strength, extrusion speed, and extrusion temperature on the elongation to break, extrusion speed, and extrusion temperature on the yield point makes the datasets ideal as variables for Radial Basis Function. The level of importance analysis in Figure 5 (d) shows that extrusion speed, extrusion temperature, and the starch content significantly influence the predicted tensile strength, elongation to break and yield point. However, the extrusion temperature displayed the most significant effect followed by the starch content. While the extruder speed has the least impact of the predicted output.

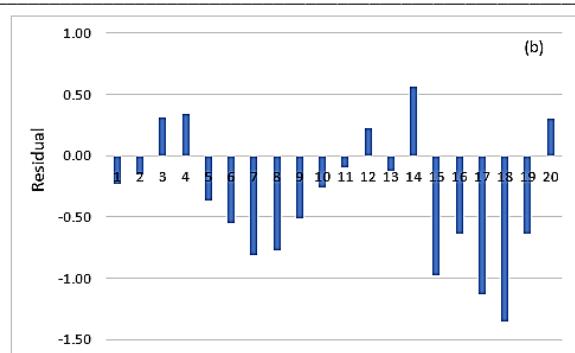
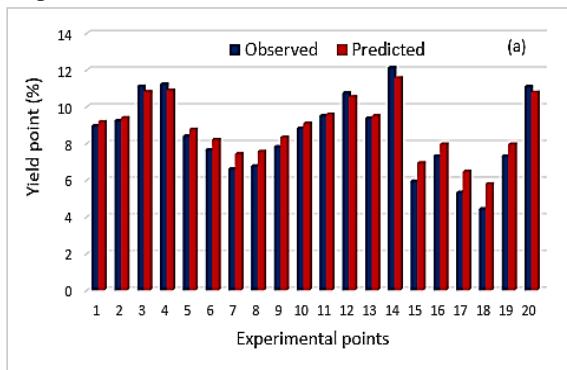
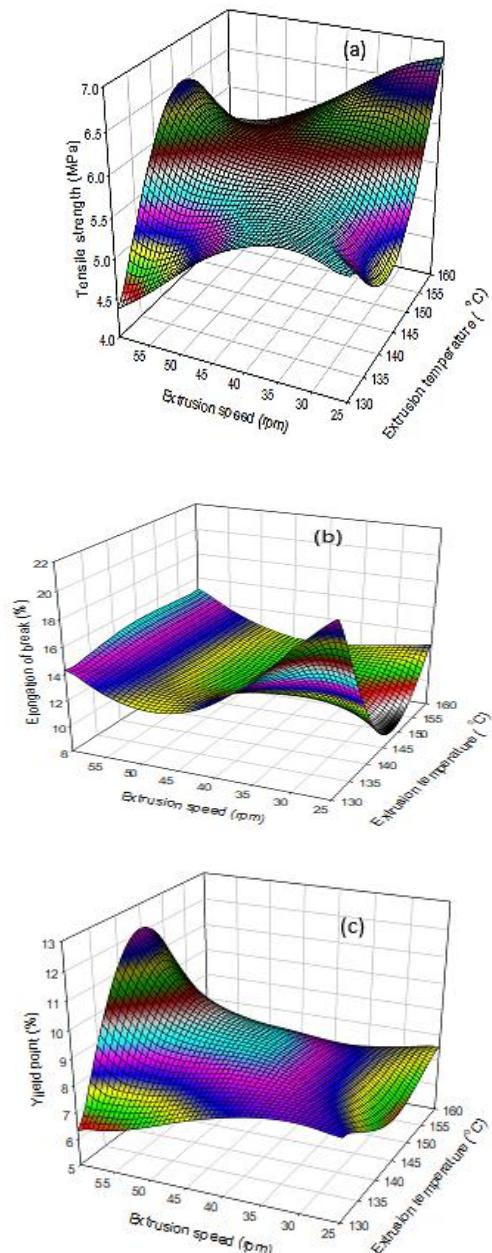


Figure 4: (a) Observed and Predicted yield point by the radial basis function (b) residual analysis of the prediction



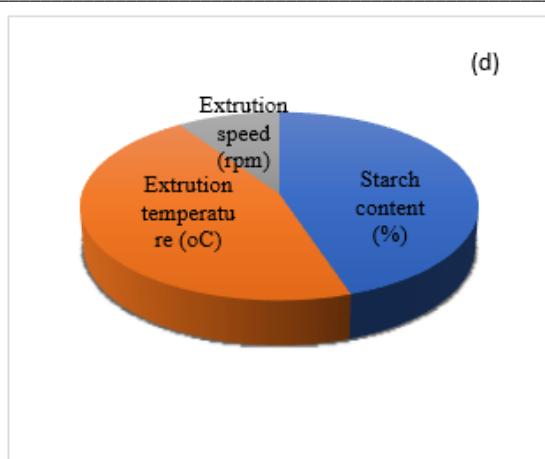


Figure 5: (a) interaction effect of extrusion speed and extrusion temperature on the tensile strength (b) interaction effect of extrusion speed and extrusion temperature on the elongation to break (c) interaction effect of extrusion speed and extrusion temperature on the yield point (d) level of importance analysis of the input parameters to the radial basis function

4. Conclusions

In this study, a data-driven Radial Basis Function approach has been employed to investigate the effect of process variables on the biodegradation of starch-plastics composite. The extrusion procedure was carried out to produce starch-LDPE composite in diverse conditions of extrusion temperature, extruding speed, and starch content. The three-dimensional plots parametric analysis has shown that the input parameters are not linked linearly to the output. For the data-driven modelling, the radial basis function has been employed using the datasets from the extrusion process. A rear spreading rule for the radial base function was used to estimate the tensile strength, elongation to break, and yield points of the starch-LDPE composite. The predictability of the Radial Basis Function of the extrusion process was proven by the R² of 0,804, 0,855 and 0,766 achieved with minimal predictive errors for the prediction of tensile strength, elongation to break and yield points. The temperature, extruder speed and starch content have been shown to impact the predicted tensile strength, elongation of break and yield points of the starch-LDPE composite considerably. But it has been shown that the extrusion temperature has the most important influence. This study may be used to understand the optimal parameter settings for a degradable material based on its mechanical characteristics.

5. Conflicts of interest

There are no conflicts to declare.

6. Acknowledgments

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