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E		**2007379**

The Known Name

Summary

Plastic waste (PW) has been one of intractable environmental dilemma for modern humankind. Traditionally, theories of plastic treatment focus on the amount and production of plastics with assessment of their managed impact on environment dependently. In order to migrate this tough problem, we combine producing of plastics and managing of plastic waste to establish a model to evaluate and reduce the plastic waste, then try to find out better solutions to prevent our cities from being flooded by plastic waste.

Firstly, we develop a plastic waste estimate model (PWEM) based on life cycle assessment (LCA) with consideration of certain factors ranging from the sources to the final management of PW, to estimating the maximal levels of single-use or disposable plastic products in a certain region or country. Linear programming and optimization methed are the core mathematical methods of PWEM, including one particular objective function and four constraint conditions. We set the amount of plastics as the target value, while we dependently explore the four possible ends of PW and formulate their impacts on environment by several functions. As a result, PWVM can put out the maximal amount of plastic products by analyzing the input digits of any region.

Secondly, to find out to what extent plastic waste can be minimized, we established an model called HSVR which combines happiness-index analysis and SVR method.

Thirdly, we promote our basic model to suit the international environment which can conclude an achievable minimal target level of global PW. We follow the precious happiness index to assess how much human life is changed, and apply the Environmental Assessment of Solid Waste Systems and Technologies (EASEWASTE) model to evaluating how the the environment is affected by plastic reduction. Moreover, for valuing the loss of multiple plastic industry, we take computable general equilibrium (CGE) model to quantify the negative effects of the target plastic production. Then we normalized the outputs and into indexs, and calculate the weight for each indicator above by the analytic hierarchy process (AHP). After that, we take a linear combination of variables that have been quantified to conclude the total impact for achieving the confined level.

Furthermore, whether the plastic waste is overloaded or the plastic products are reduced, they may impact countries unequally because of their different development level. We discuss several measures that could be taken:

1. Diversifying the standard level of plastic waste based on countriesâĂŹ level of development.

2. Drawing up a plan to encourage technical support from developed to developing countries.

Finally, we revise our original model by add a time-dependent index - Or: we expand a time sequence model (TSM) - to analyze how to approach the target minimum level following the time line by an achievable way. It should be noticed that many unexpected circumstance would definitely appear so we empirically choose most significant possibilities that may delay or accelerate the achievement process. The result are specified into a memo which can be provided for ICM. Sensitivity analysis model testing by case analyzing.

Keywords: plastic waste; estimate; LCA model; HSVR model; EASEWASTE model; AHP

Contents

1 Introduction

1.1 Background

The plastic industry can date back to1950s, over the past 60 years, the production of plastic has grown rapidly, which has surpass most other artificial materials[1]. While people then did not realize the potential negative influence of plastic usage to ecosystem, plastic waste gradually accumulated in the environment because of itâĂŹs non-biodegradable trait. Some scholar believe that plastic bags and Styrofoam containers can take up to 1,000 years to decompose[2]. 6,300Mt plastic waste has been generated in 2015, while only 9% of which had been recycled and reused. 12% of them were incinerated and the percentage of plastics that discarded in landfills or natural environment was up to 79%[1]. Plastics in nature especially in the ocean will cause a series of ecological problems. Apart form the chemical affects to organisms, plastic ingestion and entanglement are also threatening the diversity of species[3]. It is easy to imagine that if no measure is taken, human will facing severe degradation and pollution caused by enormous plastic waste.

Besides, the management of the plastic waste is one of the hardest issue on integrated municipal solid waste (MSW). There are many researches that focus on the plastic recovery routes based on the life cycle assessment approach (LCA) [4], and a few methods to assess the impact of solid waste system and technologies, which aim at develop more effective ways to migrate the plastic waste problem[5].

However, it seems that there are few researchers ever explore the valuation model of estimating the maximum use of plastics nor utility policy to reduce the usage of plastics remarkably. That indicates there is still room for further explanation in this area.

The management of the plastic waste is one of the most controversial topic in the discussion on integrated municipal solid waste area.

1.2 Restatement of the problem

Living in the age that are characterized by a series of troublesome environmental problems, such as global warming, desertification, pollution of water and poor air quality. Our team is hired to estimate the maximal permitted amount of plastic products, migrate the plastic production and reduce plastic waste. In another word, we need to answer the following questions:

1. What is the maximal level of single-use or disposable plastic products without further pollution?
2. What extent can plastic waste be reduced to?
3. What is the minimal achievable level of global single-use or disposable plastic products and what are the impact on certain facets of reaching this level?
4. How to solve the equity problem about plastic waste that arise from global crisis?
5. How to build a timeline to approuch our target level we set before and describe our exploration to ICM?

1.3 Overview of our work

For task 1, we build PWEM on the basis of LCA, and applied some logical abstractions, physical derivations, and mathematical methods to accomplished the linear programming process, then out put the estimated maximal level of plastic products.

For task 2, considering the shortage of data, we create our HSVR model to define the miximal level with least negative effects on peopleâĂŹs living standards.

For task 3, we set an achievable target level of plastic usage and apply quite a few known methods to quantify and combine the given factors for assessing the total influence of achieving our goal.

For task 4, we revise our model and provide realistic solutions for the mentioned euity issue.

For task 5, TSM is established for predicting the possible timeline and discuss possible relevant circumstances, then write a specific memo for ICM.

2 Assumptions and justifications

To simplify the problem, we strive for the following assumptions:

- **The mass of annual plastic production equals to that of the annual plastic waste.** On the one hand, every pound of plastic produced will turn into waste. On the other hand, the lifeline of most sorts of plastic is under 20 so that given situation will not change acutely[1].
- **Throughout the life cycle of plastic, the impact of plastic on environment in use phase is negligible.** Main environment issues that are related to plastic merely when it is produced or managed[11].
- **Aiming to make plastic waste safely be mitigated, any waste should not be landfilled.** While it is extremely hard for plastic to biodegrate in solid, landfills are in great shortage.[11].
- **All the plastic waste produced will be managed.** In the long run, the NET plastic waste discarded in natural environment will approach zero by governments and NGOsâĂŹ efforts.
- **The proper quantity of pollutant emission of plastic waste should depend on the contribution of plastic industry to the gross domestic products.** The pollutant emission of plastic waste is just an ordinary part of the total emission, so the responsibility of environmental protection it takes should also be the proportional part, which is roughly estimated by the percentage of GDP that plastic industry contributes.
- All the plastic waste is mechanically sorted from plastic waste prior to incineration.
- The material recycling facilities(MRFs) that sort and upgrade the received waste stream is the only way to recycled sorted PW.

3 Linear programming based Model for maximal plastic waste estimation

We noticed that this puzzle is a maximization problem with several limiting conditions. So linear programming(LP) must be the best way to approach the answer we want.

3.1 Basic Theories

PLC theory tell us the specific stage of plastic life will impact environment, while LCA theory provide us a tool to quntify impacts of recyclement. LP and simplex algorithm(SA) are mathematical methods, and by former we establish our objective functions and constraints while by the latter we get the optimal solution for LP.

3.1.1 PLC theory

To guarantee that the maximal usage or producing of plastics will not damage the environment further, we identify the parts of plasticsâĂŹ life cycle that might cause damage to the environment, as is shown in figure 1. Consider a revised product life cycle (PLC) theory: as every product has its life cycle from R&D(**esearch and development**) to launching on market to decline and exit the market as an end, plastics also cycle from products to waste. For plastic products from various source, their producing processed may affect the environment as well as their managing courses. The model expand based on the plastic life cycle theory.

Figure 1: The parts of plasticsâĂŹ life cycle that might cause damage to the environment.

3.1.2 Linear programming

Linear programming (LP) is a tool for solving optimization problems for which we do following:

1. We attempt to maximize (or minimize) a linear function of the decision variables which is called the objective function.
2. The values of the decision variables must satisfy a set of constraints. Each constraint must be a linear equation or linear inequality.
3. A sign restriction is associated with each variable. For any variable xi, the sign restriction specifies that xi must be either nonnegative (xiâĽě0) or unrestricted in sign (urs).

So we try to set our objective function as the permitted maximal amount of plastic; and abstract the most limited conditions into constraints.

3.2 Notations

The notations used are shown in table 1.

Table 1: Notations

Symbols	Definition
s_i	Annual certain plastic production.
N_i	The number of $CO2$ generated by the combustion of 1 molecule specific plastic unit.
EA	Emission to air.
EW	Emission to water.
EC	Emission of CO_2.
TEA	Total emission to air.
TEW	Total emission to water.
TEC	Total emission of CO_2.
CEA	Compensatory emission to air of recovery process.
CEW	Compensatory emission to water of recovery process.
SM	Plastic waste into marine.
M	The quantity of annual management of marine plastic.
V_air	Total available air of a specific country/region.
V_water	Total available water of a specific country/region.
σ	Proportion of incinerated plastic waste.
μ	Compensate.
θ	The percentage of GDP plastic industry contributes, quantified by coefficient.
ι	Tossil fuel consumption percentage. Generally, ι equals 4‰.

3.3 Qualify the impact on the environment

3.3.1 Producing process

According to the first assumption, we consider the annual production and waste as the same variable S. And naturally it is divided into various sorts of plastic.

$$S = \sum_i s_i \tag{1}$$

Note that, i rrepresents a sort of plastic and s_i is the annual production of this sort of plastic. All sorts of plastic taken into account are PVC, PE, PP, PS, PET, PUR and PC[11].

To quantify to what extent plastic waste impact the environment in its life cycle, we use Emissions air(EA) and Emissions water (EW) to measure emissions, whose units are Units of Polluted Water (UPW/ton) and Unit of Polluted Air with the production of a ton of plastic(UPA/ton). UPW is the number of cubic meters of water polluted up to the European drinking water standard by the production of 1 tonne of the material. UPA is a similar measure for air and gives the cubic meters of air needed to dilute the emissions to the European maximum acceptable concentration (MAC)[11]. Then the Emissions of water and air can be formulated below:

$$TEA^{\alpha} = \sum_i s_i \times EA_i^{\alpha} \tag{2}$$

$$TEW^{\alpha} = \sum_i s_i \times EW_i^{\alpha} \tag{3}$$

Given the energy consumption per unit of plastic production, we set energy consumption of specific plastic production as Ei the proportional coefficient of carbon emission per unit of energy consumption as k, total emission of CO2 can be calculated as:

$$TEC^{\alpha} = \sum_i s_i \times E_i^{\alpha} \tag{4}$$

3.3.2 Managing process

When it comes to plastic waste management, there are three possible fates for managed plastic waste: being recycled, being incinerated and being discarded(be landfilled or be discarded in natural environment). According to the third and fourth assumption, we assume there are only two managing method: incinerating or recycling.

For the proportion of recycled PW, they are recycled by The material recycling facilities(MRFs). The mechanical separation removes polyethylene terephthalate (PET) and high density polyethylene(HDPE) bottles at high efficiency, which are sent to recycling, and other minor high calorific fluxes sent to energy recovery in cement kilns[4]. After that we could get certain recovery rate, we set this rate as $1 - \sigma$, the proportion of incinerated part is σ.

Firstly, we apply a classical environmental assessment method: life cycle assessment (LCA), to evaluate the environmental issues associated with solid wast with solid waste management[5].

Secondly, we simplify and abstract the many categories of LCA into three categories based on data availability and computational matching: EA, EW and EC.

Furthermore, because the recycling technology(MRFs) saves this part of PW from incineration and put recycled products into market again, while the harmful emissions from recycling are often less than the emissions from incinerating this part of the plastic[15]. There are digital supports that reveal the positive influence about of recovery, as is shown in figure 2 and figure 3. So we calculate this different value as compensatory emissions.

Then the environmental impact of plastic waste management can be calculated:

$$TEA^{\beta} = \sigma \sum_i s_i \times EA_i^{\beta} - (1 - \sigma) \sum_i s_i \times CEA_i^{\beta} \tag{5}$$

$$TEW^{\beta} = \sigma \sum_i s_i \times EW_i^{\beta} - (1 - \sigma) \sum_i s_i \times CEW_i^{\beta} \tag{6}$$

Figure 2: Net eutrophication potential.

Figure 3: Net global warming potential.

Apart from above analysis, although we assume that all the plastic waste discarded in natural environment will be managed, too much discarded plastic waste (even if temporarily) will notably do harm to marine ecosystem[3]. Thus itâĂŹs necessary to estimate the mass of plastic waste(symbolized by SM) inputs from land into the ocean, given specific total plastic waste.

$$SM = \varsigma \sum_i s_i \tag{7}$$

For the plastic waste that has been incinerated, in the process of incineration, we take the emission of greenhouse gases CO_2 (EC) to represent itâĂŹs contributions to global warming:

$$TEC^{\beta} = \sigma \sum_i s_i \times N_i - \mu(1-\sigma) \sum_i s_i \tag{8}$$

3.4 Constraints given by environmental carrying capacity

Firstly, according to the fifth assumption, the pollutant emission constraints are roughly estimated by the percentage of GDP plastic industry contributes, quantified by coefficient θ.

$$TEA^{\alpha} + TEA^{\beta} \leq \theta V_{air} \tag{9}$$

$$TEW^{\alpha} + TEW^{\beta} \leq \theta V_{water} \tag{10}$$

Secondly, when it comes to greenhouse gas CO_2, itâĂŹs more propriate to use its fossil fuel consumption percentage to set the restraint because the fossil fuel combustion is the principal factor of the global warming, rather than natural carbon cycles[11].

$$EC \leq \iota V_{CO_2} \tag{11}$$

Last but not least, considering current quantity of plastic discarded in the ocean donâĂŹt exert severe impact on marine ecosystem, we regard zero net input into the sea an acceptable circumstance for marine environment, i.e. annual plastic waste input canâĂŹt beyond the quantity of annual management of marine plastic(symbolized by M).

$$SM \leq M \tag{12}$$

3.5 Finally model base on linear programming

Objective functions:

$$S = \sum_{i} s_i \tag{13}$$

subject to:

$$\begin{cases} TEA^{\alpha} + TEA^{\beta} \leq \theta V_{air} \\ TEW^{\alpha} + TEW^{\beta} \leq \theta V_{water} \\ EC \leq \iota V_{CO_2} \\ SM \leq M \end{cases} \tag{14}$$

3.6 Data Analysis

In this section, we will combine the data from China to further introduce the model.

China is a developed country which emission largest amount of PW to marine, which may be sensitive to change of plastic amount. So we apply our model to the practical examples of China. Table 2 lists seven disposable plastics mainly used in China. We consider them as model variables s_i.

We used data from the National Bureau of Statistics of China[16] and obtained parameters closely related to the model.

The objective function can be defined as:

$$S = s_1 + s_2 + s_3 + s_4 + s_5 + s_6 + s_7 \tag{15}$$

Given the compensatory emission of recycling process is a relatively vague variable for three reasons:

Table 2: The main types of disposable plastics used in China

Variable	Plastic types
s1	PVC
s2	PE
s3	PP
s4	PS
s5	PET
s6	PUR
s7	PC

1. The proportion of recycled PW is relatively small in realistic practices.
2. Most regions of China are not developed enough to have the advanced technology of MRFs to manage PW.
3. Chinese PW sorting and managing system are not perfect.

Given all above realistic situations, the compensite emission to water and air of recycling process should be deemed as zero, so is the compensite coefficient of CO_2.

4 To what extent plastic waste can be reduced

At present, the global use of plastics has exceeded the upper limit of environmental tolerance, which poses a huge threat to the ecological environment. In section 4, We propose a model of Happiness based on SVR[6], which we call HSVR. Using HHSVR, we will explore the impact of the use of plastic on human living standards, and try to reduce the amount of plastic used as much as possible without affecting much of human living standards.

Our starting point is straightforward: the use of plastic is essential, and reducing the use of plastic will inevitably affect the living standards of local people. By analyzing the characteristics of different regions (especially the amount of plastics produced) and the people's living standards, we find out the relationship between the amount of plastics produced and the people's happiness index. Based on this, we can analyze how much plastic production we can reduce without significantly reducing the happiness index.

The following of this section will first briefly introduce the method we use, and then obtain a specific regression model based on the Global Happiness Report[7] and plastic production in each region[8].

4.1 SVR algorithm

Support vector regression(SVR) is an application of SVM (support vector machine) to regression problems. Support vector machines construct a hyperplane or a series of hyperplanes in a high-dimensional or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, using a hyperplane to achieve a good segmentation can make the closest training data points have the largest separation distance in any category. This is because usually a larger margin can have a lower generalization error of classifier[9].

Given training vectors $x_i \in R^p, i = 1, \cdots, n$, and a vector $y \in R^n$. $\varepsilon - SVR$ solves the following primal problem:

$$\min_{\omega,b,\zeta,\zeta^*} \frac{1}{2}\omega^T\omega + C\sum_{i=1}^{n}(\zeta_i + \zeta_i^*) \tag{16}$$

subject to

$$y_i - \omega^T\phi(x_i) - b \leq \varepsilon + \zeta_i \tag{17}$$

$$\omega^T\phi(x_i) + b - y_i \leq \varepsilon + \zeta_i^* \tag{18}$$

where $\zeta_i, \zeta_i^* \geq 0, i = 1, \cdots, n$.

Its dual is

$$\min_{\alpha,\alpha^*} \frac{1}{2}(\alpha - \alpha^*) + \varepsilon e^T(\alpha + \alpha^*) - y^T(\alpha - \alpha^*) \tag{19}$$

subject to

$$e^T(\alpha - \alpha^*) = 0 \tag{20}$$

where $0 \leq \alpha_i, \alpha_i^* \leq C, i = 1, \cdots, n$, e is the vector of all ones, $C > 0$ is the upper bound, Q is an n by n positive semidefinite matrix, $Q_{ij} \equiv K(x_i, x_j) = \phi(x_i)^T\phi(x_j)$ is the kernel. Here training vectors are implicitly mapped into a higher (maybe infinite) dimensional space by the function ϕ. ϕ can be linear, polynomial, sigmoid or others.

The decision function is:

$$\sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x_i, x) + \rho \tag{21}$$

For more details, please refer to [6].

4.2 Detailed analysis

In this section, we will introduce the quantitative standard of happiness, analyze this problem, and use SVR to get the function of happiness and plastic production $\hat{f}$ so that $\hat{f} : X \mapsto y$, where X is a vector in $\mathcal{X} = \mathcal{R}^d$, including a dimension of plastic production.

4.2.1 The quantitative standard of happiness

We use the happiness quantification standard used by the World Happiness Report[7], where the happiness scores and rankings use data from the Gallup World Poll. The scores are based on answers to the main life evaluation question asked in the poll. This question, known as the Cantril ladder, asks respondents to think of a ladder with the best possible life for them being a 10 and the worst possible life being a 0 and to rate their own current lives on that scale. The scores are from nationally representative samples for the years 2013-2016 and use the Gallup weights to make the estimates representative.

Obviously, people's happiness depends not only on the amount of plastic produced. In fact, plastic production and waste account for only a small part of the factors affecting people's happiness. There are six factors usually concerned to be relevant to happiness: economic production, social support, life expectancy, freedom, absence of corruption, and generosity. The data that estimates the extent to which each of six factors contribute to making life evaluations higher in each country than they are in Dystopia, a hypothetical country that has values equal to the worldâĂŹs lowest national averages for each of the six factors, is also used to as part of the input of HSVR, with some preprocessing:

$$x^* = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{22}$$

where x_max, x_min is the maximum and minimum of the original data, respectively.

Note that the first preprocessing maps the data to $[0, 1]$. The preprocessing step will erase the differences between the data formats and make the characteristics of the data more obvious.

4.2.2 Plastic Emphasized

The impact of the production and use of plastic on happiness should be far less than that of the other six factors mentioned above, which means that the input to the problem should be a weighting of all seven factors:

$$X = (\epsilon_1 x_1, \epsilon_2 x_2, \epsilon_3 x_3, \epsilon_4 x_4, \epsilon_5 x_5, \epsilon_6 x_6, \epsilon_7 x_7) \tag{23}$$

However, what we need to find is mainly the relationship between plastic production and happiness, so we give plastic production a sufficiently high weight, where $\epsilon_i = 1, i = 1, \cdots, n$.

The lack of data[10] in research on plastic production and consumption has always been a serious problem. To the best of our knowledge, there are no specific statistics on the amount of plastic used in many regions, especially in developing countries. This means that our research will face problems of insufficient data volume and potential data imbalances. Based on this, we chose SVR as our classifier, because SVR has the following characteristics[9] and is suitable for solving this problem:

- Effective in high dimensional spaces.
- Still effective in cases where number of dimensions is greater than the number of samples.
- Versatile: different Kernel functions can be specified for the decision function.

4.3 Model parameter selection

We randomly selected 20 countries from [7] and [8] as our training set as our training set. These countries include countries that consume more plastic, such as China and India, and developed countries, such as the United States and the United Kingdom. In combination with the training situation, we adjusted the model in real time to obtain the optimal model.

4.3.1 Model performance evaluation

To evaluate the performance of the model, we used k-fold cross-validation[12]. In k-fold cross-validation, the original sample is randomly partitioned into k equal sized subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining k âĹŠ 1 subsamples are used as training data. The cross-validation process is then repeated k times, with each of the k subsamples used exactly once as the validation data. The k results can then be averaged to produce a single estimation. The advantage of this method is that all observations are used for both training and validation, and each observation is used for validation exactly once. 10-fold cross-validation is commonly used[13], but in general k remains an unfixed parameter.

We choose the Euclidean norm of the regression value and the true value(or the mean square error, MSE) to measure the quality of the regression result:

$$MSE = \frac{1}{k}\|y - \hat{y}\|_2 \tag{24}$$

where y is the true value, and $\hat{y}$ is the regression value.

4.4 Specific model parameters

We have implemented four kinds of kernel function[9] of SVR and verified them separately.

The four cores are:

- linear: $\langle x, x' \rangle$
- polynomial: $(y\langle x, x' \rangle + r)^d$.
- rbf: $e^{-\gamma\|x-x'\|^2}$.
- sigmoid: $\tanh(\langle x, x' \rangle + r)$.

Due to the high feature dimension of our training set and the small number of training samples, in general, the effect of the linear kernel should be better. The results in figure 4 also illustrate this:

As can be seen from the figure, the results of linear and rbf are much better than the results of sigmoid and polynomial, which all converge to an error close to 0. In fact, the training error of the linear kernel is on the order of 10^{-2}. Moreover, the linear kernel has already converged by training about ten samples, which shows that our data volume is sufficient for our model.

4.5 Predict minimum plastic usage in an area

From the above analysis, we find that the linear kernel function has the best fitting effect, indicating that the plastic consumption has a linear relationship with the living standard. This is consistent with per capita plastic consumption in different regions. Table 3 is a table of plastic consumption in different regions. Intuitively, the consumption of plastic is positively related to the living standard of the region. Developed regions generally have higher plastic consumption. Of course, this is also related to other factors. These are reflected in our model.

Figure 4: Training results of different SVR kernel functions.

Table 3: Plastic consumption in different regions

Area	**Plastic consumption (1 ton per 100,000 people)**
China	1316.1
North America	1571.9
Asia Pacific	657.1
Western Europe	2870.6
India	251.9
Middle East	580.4
Central and South America	308.8
Central and Eastern Europe	1468.4
Africa	99.8
Japan	812.9

Based on this conclusion, we found that reducing the amount of plastic used will inevitably affect people's happiness. Therefore, we need to make a compromise between happiness and environment. This is undoubtedly a very painful thing. Therefore, we need to find a threshold on the tolerance of the regions κ. κ is such a value: in a specific area, if happiness $\Gamma = \hat{f}(X) < \kappa$, it is not worthwhile to reduce consumption. Note that $\hat{f}$ is trained in section 4.3. κ can be derived from historical data and is closely related to each place.

Unfortunately, many people are unwilling to pay a lot for environmental protection[14], as is shown in figure 5. So we carefully set this value to 1% of the existing happiness index.

For example, figure 6 shows this relationship in the US. Currently, plastic consumption in the United States is 1571.9 tons per 100,000 people. If America's tolerance for happiness is 7.263, then the minimum plastic consumption in the United States should be 500 tons per 100,000 people. If plastics production is required to fall below this limit, it will cause more problems and outweigh the benefits.

Figure 5: Happiness-Plastic curve of US.

Figure 6: Happiness-Plastic curve of US.

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