FORECASTING E-WASTE IN PRESENCE OF LIMITED DATA

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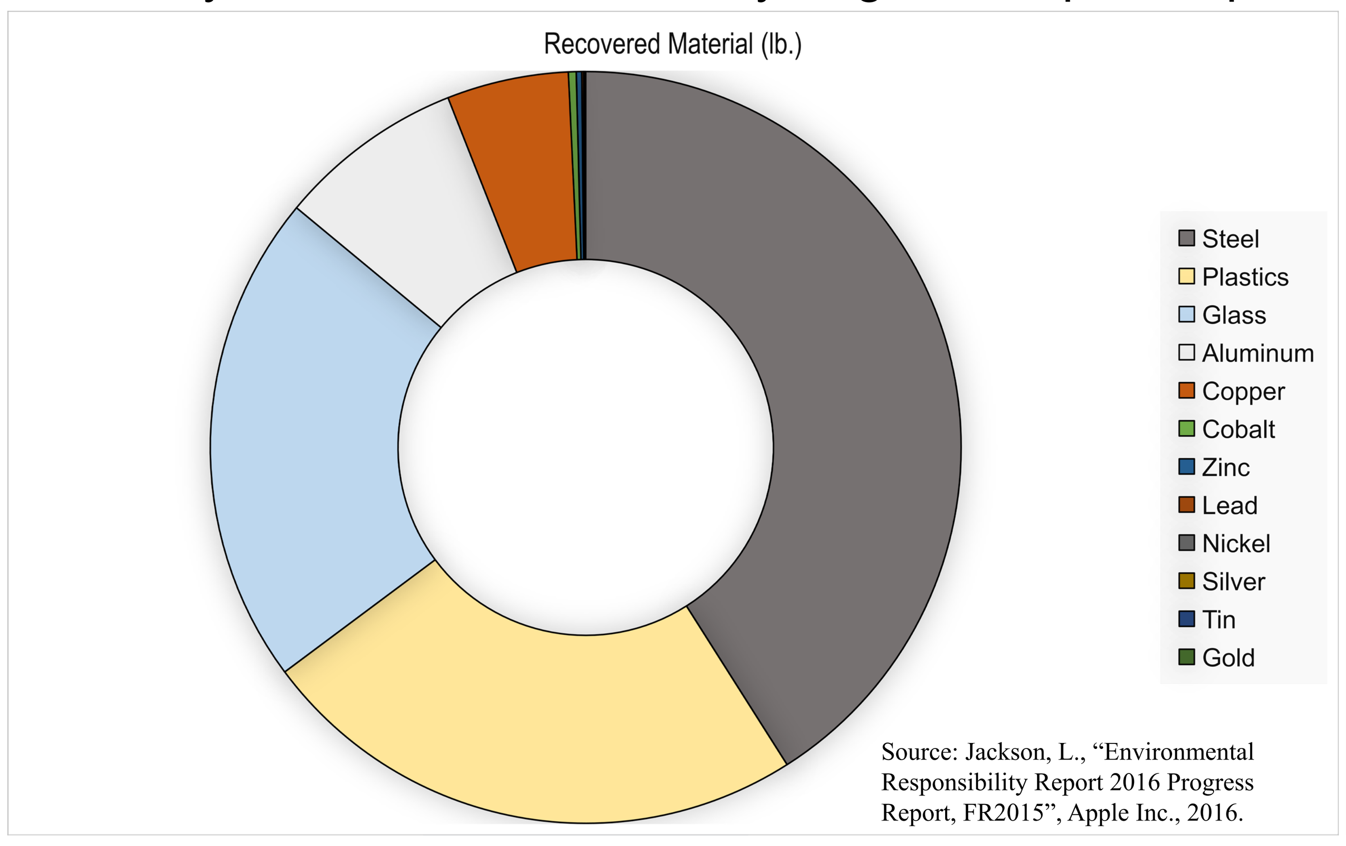
Objectives

Electronic waste (E-waste) has emerged as one of the fastest growing municipal solid waste streams in the United States due to rapid changes in technology and increasing consumer demand.
Accurate estimations on the amount of e-waste might help in increasing the efficiency of waste collection, recycling and disposal operations.



> "Data! Data! Data!" he cried impatiently. "I cannot make bricks without clay."
> *Adventure of the Copper Beeches* - Sir Arthur Conan Doyle

Figure 1. Recovered material for reuse through take-back initiatives in 2015

The literature offers various methodologies focusing on prediction of e-waste generation. Among these, Grey Modeling (GM) approach has drawn attention due to its ability to provide meaningful results with utilizing relatively small-sized data. In order to improve the overall success rate of the approach, several GM-based models have been developed over the years. **The performance of these models, however, heavily rely on the parameters used with no established consensus regarding the suitable criteria for better accuracy.** This study presents a novel GM approach improved by Particle Swarm Optimization (PSO). A case study utilizing Washington State e-waste data is provided to demonstrate the comparative analysis proposed in the study.

Methodology: Grey Modeling

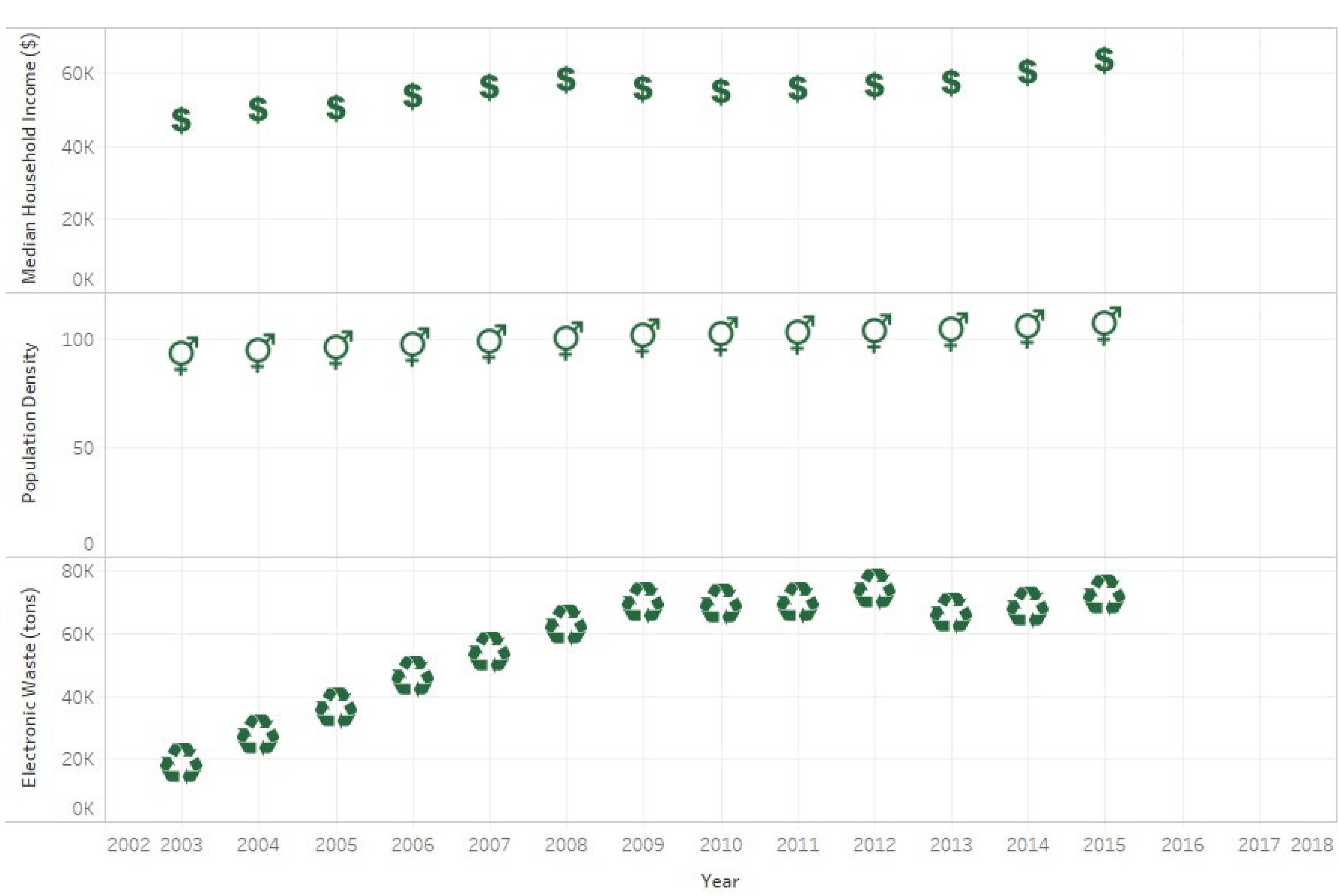
Since its introduction by Deng (1989), various GMs have been developed over the years by the researchers to deal with the limited data issues in forecasting:

- The characteristics of the data determines the best fitted GM.
- The parameters used in the model directly affect the forecasting accuracy.

Forecasting E-Waste Generated in WA

> "Data is like garbage. You'd better know what you are going to do with it before you collect it." – Mark Twain

Figure 2. Population Density, Median Household Income and E-waste in WA

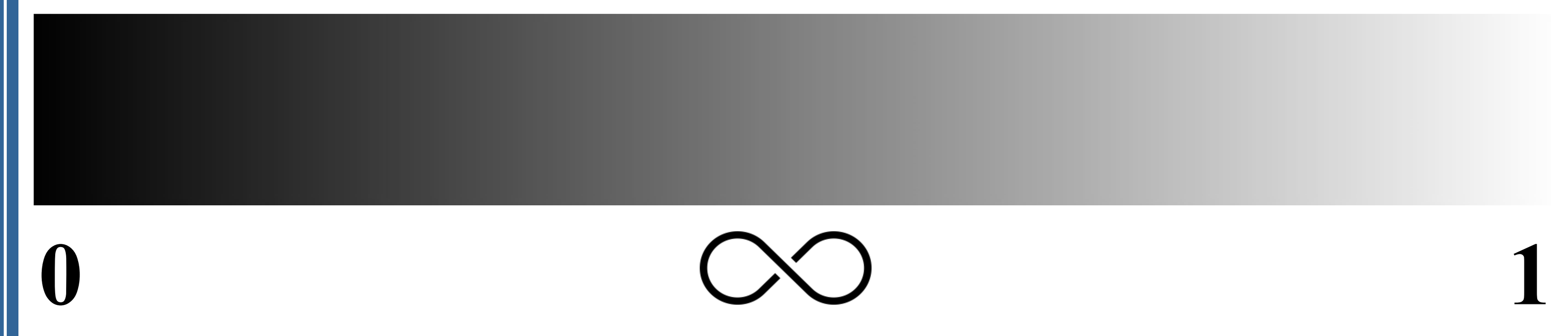


Grey Model with Convolution Integral GMC(1,n)

The original GM(1,n) is essentially the combination of differential equations, time series analysis and linear regression.

GMC(1,n) first proposed by Tien (2005) also integrates Convolution Integral into the original GM. In these models, background value coefficient $\omega \in [0, 1]$ represents the "greyness" between two data points (commonly, 0.5).

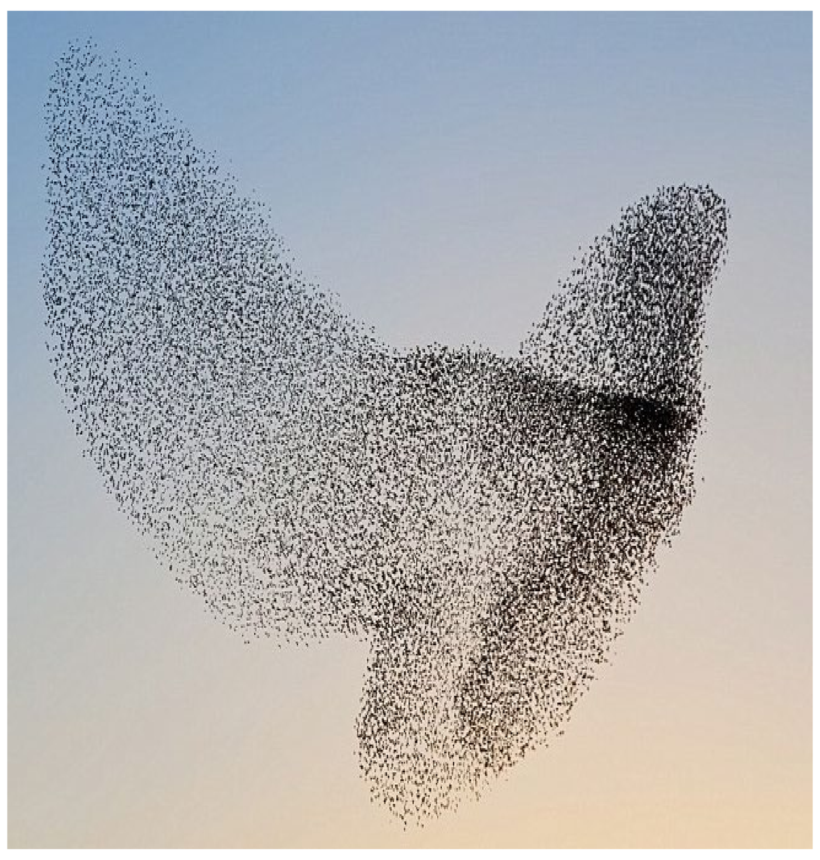
How many shades of grey ?



Optimizing the ω value can improve the results. Particle Swarm Optimization can be utilized to find the optimal/near optimal ω value.

Particle Swarm Optimization

PSO is inspired by the social behavior metaphor of the birds. Similar to Genetic Algorithm, Swarm is the population, Particle is the chromosome. Particles in the swarm co-operate with each other.

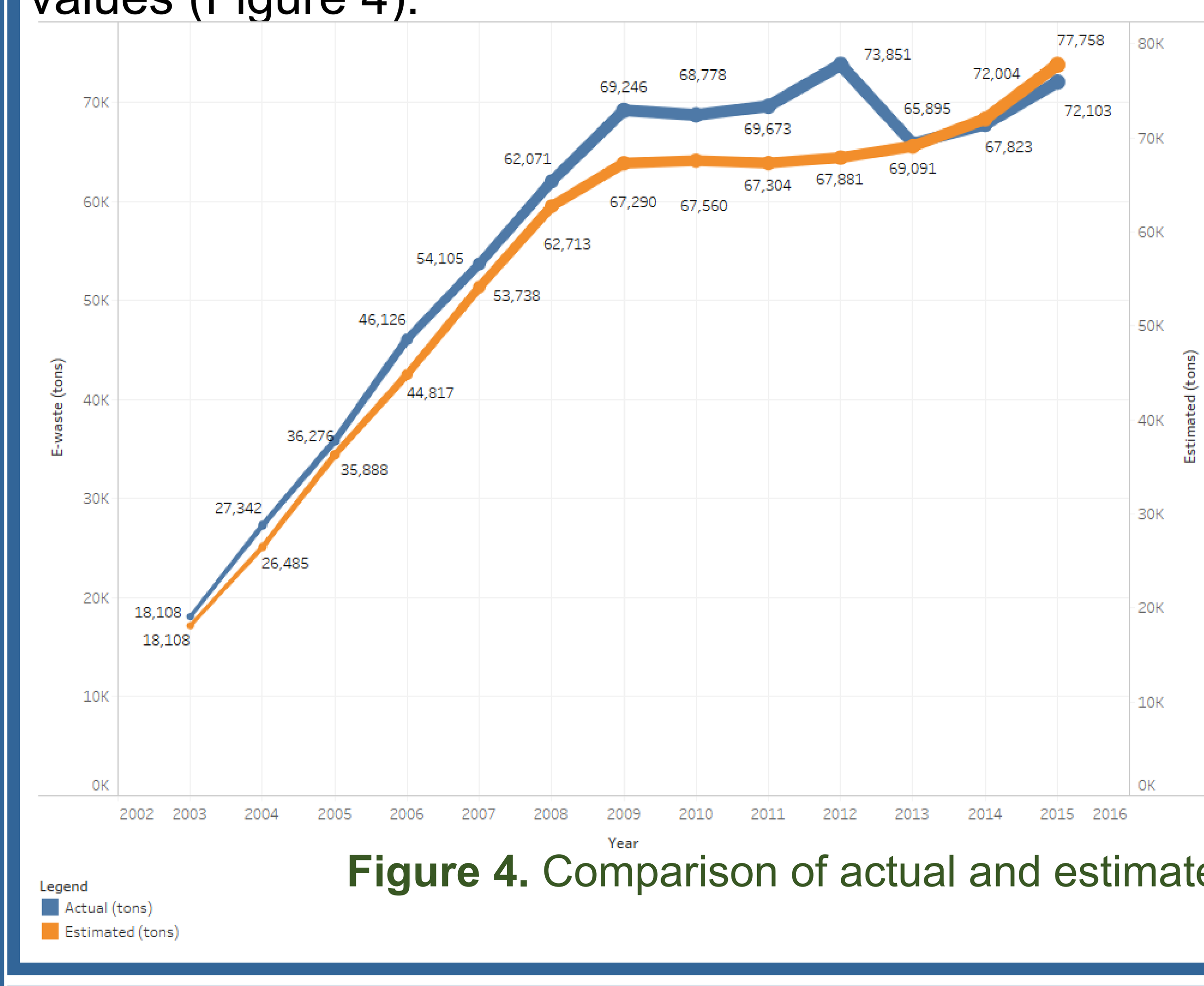


```
[x*] = PSO()
P = Particle_Initialization();
For i=1 to it_max
   For each particle p in P do
      fp = f(p);
      If fp is better than f(pBest)
            pBest = p;
      end
   end
   gBest = best p in P;
   For each particle p in P do
    v = v + c1*rand*(pBest – p) + c2*rand*(gBest –p);
      p = p + v;
   end
end
```

Figure 3. Particle Swarm Optimization

Results: E-Waste Forecast in WA

All computations are executed on Matlab2017b. The optimal/near optimal ω values are obtained as 0.273, 0.109, 0.030 for Population Density, Median Household Income and E-waste, respectively. Subsequently, the estimated e-waste values are obtained via utilizing ω values (Figure 4).



Year	Actual	Estimated
2003	18108.186	18108.200
2004	27341.564	26485.360
2005	35887.901	36276.317
2006	46126.412	44816.677
2007	53737.509	54105.295
2008	62071.464	62713.059
2009	69246.269	67289.843
2010	68777.911	67560.175
2011	69673.018	67304.155
2012	73851.238	67881.383
2013	65894.784	69090.753
2014	67822.933	72004.364
2015	72103.408	77758.017

Figure 4. Comparison of actual and estimated values

Conclusions and Future Research

- **The application proves that even in the presence of missing/inaccurate/limited data, accurate forecasting can be conducted.**
- A comparative analysis among Multiple Linear Regression (MLR), traditional GM and GMC is conducted to obtain the Root Mean Square errors (RMSE) of each model.
- With (RMSE-GMC = 2,927.44), GMC outperformed the other two methods (RMSE-GM=3567.69, RMSE-MLR=5956.68).
- **Directions for further research include the utilization of Bernoulli model to improve forecasting accuracy since the data characteristics form a saturated distribution.**

References

- Deng, J.L., 1989. Introduction to Grey system theory. J. Grey Syst. 1, 1-24.
- Tien, T.-L., 2005. The indirect measurement of tensile strength of material by the grey prediction model GMC (1, n). Measurement Science and Technology 16, 1322.
- Ma, X., Liu, Z., 2017. The GMC (1, n) model with optimized parameters and its application.