Analysis of Italian Waste Management Data via Non-Stationary Signal Analysis Methods

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Abstract

This study presents the two-dimensional Fast Iterative Filtering (2D-FIF) technique, an advanced tool in signal processing, and explores its application to the analysis of economic data pertaining to waste management. The overarching objective is to contribute to the formulation of innovative, data-driven guidelines aimed at promoting the transition toward a Circular Economy.

Italy offers a particularly rich case study, given its complex and heterogeneously distributed waste management systems, shaped by structural, technical, political, and socioeconomic variabilities across regions. This diversity enables an empirical investigation into the influence of numerous interacting variables on system performance. However, the underlying data are intrinsically non-stationary in both time and space, rendering traditional signal processing methodologies—such as those based on Fourier and wavelet analyses—less effective in capturing the nuanced dynamics involved.

Over the past two decades, several novel approaches tailored to non-stationary signal analysis have emerged, among which Fast Iterative Filtering has distinguished itself due to its solid mathematical grounding. The method is not only provably convergent and robust to noise but also computationally efficient. Its efficacy has been demonstrated in various domains including physics, engineering, and biomedical sciences.

In the present we briefly review recent non-stationary signal processing techniques, in particular the 2D Fast Iterative Filtering, and we will apply them to Italian waste management datasets, with the goal of uncovering latent relationships between system configurations and operational outcomes. The ultimate ambition is to furnish policymakers and local administrators with actionable insights and empirically-grounded best practices to enhance waste management efficacy and further the goals of the Circular Economy.

Keywords

Non-stationary signal processing, Circular Economy (CE), waste management.

1. Introduction

In many applied fields of research, like Geophysics, Medicine, Engineering, Economy, and Finance, to mention a few, classical challenging problems are the identification of hidden information and features contained in a given signal, like quasi-periodicities and frequency patterns, as well as the extraction of all the different components contained in it.

Standard methods based on Fourier and Wavelet Transform, historically used in Signal Processing, proved to be limited in the presence of nonlinear and non-stationary phenomena [1, 2]. For this reason,

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in the last two decades, several new nonlinear methods have been developed by many research groups around the world, and they have been used extensively in several applied fields of research.

In this work, we briefly review the pioneering technique Hilbert-Huang Transform (a.k.a. Empirical Mode Decomposition method) and discuss its known limitations. Then, we introduce the Fast Iterative Filtering technique [3] and its generalization to handle multidimensional non-stationary signals in the so called 2D Fast Iterative Filtering (FIF2) [4, 5]. We will discuss these methods theoretical and numerical properties and apply this methodology to the analysis of Italian waste management data with the goal of identifying hidden connections between the setting up of local systems and their actual performance, providing local administrators and policymakers with new insights and best practices on how to optimize waste management.

Waste management represents nowadays a fundamental issue in the transition from a linear to a circular economy (CE) model both at international and national levels. The 2030 Agenda for Sustainable Development, and in particular goal 12 "Ensure sustainable patterns of production and consumption", aspires with goal 12.5 to reduce waste production through prevention, reduction, recycling and reuse. Moreover, goal 11 "Make cities and human settlements inclusive, safe, resilient and sustainable" aims with goal 11.6 at reducing the adverse per capita environmental impact of cities, paying special attention to municipal and other waste management. According to the World Bank, annual waste generation is estimated to grow by 70% by 2050 [6]. In 2020, European Union (EU) total waste generation reached 2.3 million tons, around 4.8 tons per capita, and municipal solid waste (MSW) accounts for approximately 10% of the total waste generated in the EU27 [7]. Across Europe, differences in the municipal waste generation exist among and within countries. This is due to differences in countries economic conditions as well as in countries waste collection and management characteristics [8]. Since 2008, the Waste Framework Directive [9] has designed strategies and principles for sustainable waste management. The 2020 EU Circular Economy Strategy Action Plan (CESAP) established a policy framework aligned with the European Green Deal to achieve a cleaner and more competitive economy [10] identifying measures to achieve resource-independent economic growth, by reducing resource extraction and waste produced. The shift towards a circular economy perspective, therefore, heavily relies on virtuous and sustainable waste management [11]. Implementing a sustainable and responsible waste management system incorporating the triple bottom line (TBL) perspective [12, 13, 14] means to set goals and evolve toward more sustainable models for the "business" at hand, thus producing positive impacts for environment, profit and people. In a nutshell, sustainable waste management services can generate profit while also addressing waste issues that threaten the environment and communities. In this context, the Italian Legislative Decrees 22/1997 and 152/2006 (the Environmental Code), integrated by the Decree 2005/2010, which regulate waste management, proposed ambitious goals with the aim of improving waste management procedures and reducing waste effects on both public health and environment. More specifically, the Environmental Code set separate waste collection (SWC) targets and associated time frames for their achievement, establishing a graduated path for the SWC objectives (35% by 2006, 45% by 2008 and 65% by 2012), to encourage recycling and to reduce the amount of waste in landfills [15]. Italy, from this viewpoint, represents an important case study because it encompasses highly locally differentiated waste systems due to structural, technical, political, and socioeconomic differences across regions, allowing to verify the effects of a wide set of variables and values on the performance of waste management [10]. Thus, although this study focuses on the Italian waste sector data, it could provide tools and knowledge on issues relevant to assess waste sector analysis in several other European countries.

2. Data and Method

Regarding the data, in a TBL framework, we considered not only environmental aspects (waste generation) but also economic (service costs) and social (separate collection) performances. To this purpose, we examined variables able to catch the three essential dimensions (environmental, economic and social) of municipal waste management sustainability at Italian municipal level. We collected the following data for 2023 from Istituto Superiore per la Ricerca e la Protezione dell'Ambiente (ISPRA) public dataset

- separate collection rate (percentage);
- total waste produced per inhabitant (tons);
- mixed waste produced per inhabitant (tons);
- cost for mixed waste collected per inhabitant (euro);
- cost for separated waste collected per inhabitant (euro);
- cost for total waste management per inhabitant (euro).

As costs, we included three kinds of costs relevant in urban waste management: total cost, cost for mixed waste managed, and cost for separated waste managed. The costs for the management of mixed municipal waste include street sweeping and washing costs, collection and transportation costs, treatment and disposal costs, and other costs, relating to the management of mixed municipal waste. The costs for the management of the separate collection include costs of separate collection of individual materials, treatment and recycling costs. The total cost includes the cost for management mixed and sorted waste along with administrative, collection and litigation, general management, and other costs such as the amortization, and remuneration of capital.

Regarding the method, the seminal work of Huang et al. in 1998 introduced the Empirical Mode Decomposition (EMD) method [1], a groundbreaking approach for the analysis of nonlinear and non-stationary signals. EMD operates by decomposing a signal into a finite set of oscillatory modes, termed Intrinsic Mode Functions (IMFs). These IMFs are characterized by two principal conditions: (i) the number of extrema and zero crossings must either be equal or differ at most by one, and (ii) at any point in time, the mean of the upper and lower envelopes—defined via spline interpolation through local maxima and minima—must vanish. The decomposition is achieved through a sifting process in which local means, formed by these envelopes, are iteratively subtracted from the signal.

While EMD has proven effective in a broad range of applications, it is not without limitations. Notably, its dependence on spline-based envelope interpolation, the absence of a solid mathematical foundation, and issues related to mode mixing have spurred the development of alternative methodologies [16, 17, 18, 19]. Over the past two decades, various nonlinear techniques have been proposed to address these shortcomings, as exemplified in [20, 21, 22, 23].

Among the alternatives, Iterative Filtering (IF) stands out for its structural similarity to EMD and for being the only method in this group that does not impose a priori assumptions on the signal—such as the number of IMFs or the choice of decomposition basis. The key distinction lies in how the local average is computed. Rather than employing envelope interpolation, IF defines the moving average $\mathcal{M}(f)(x)$ of a signal f through convolution with a compactly supported filter w, as follows:

$$\mathcal{M}(f)(x) = \int_{-L}^{L} f(x+t)\, w(t)\, dt, \qquad (1)$$

where L denotes the half-length of the filter's support. Crucially, the filter length L is determined in an adaptive manner, based on intrinsic features of the signal—typically derived from the distribution of its extrema or its local spectral content [24, 25]. This adaptive mechanism imparts a nonlinear character to the IF method, rendering it responsive to the local structure of the signal.

Building on IF, the Fast Iterative Filtering (FIF) algorithm was introduced to enhance computational efficiency by leveraging the Fast Fourier Transform (FFT). FIF retains the adaptivity of IF while dramatically reducing the computational burden, thus enabling real-time processing and the treatment of high-dimensional signals. Furthermore, FIF permits the selection of specific filter profiles, such as those derived from the Fokker–Planck equation, which ensure both smoothness and compact support of the filter function.

Subsequent advancements have extended FIF to increasingly complex data modalities. These include the Multivariate Fast Iterative Filtering (MvFIF) algorithm for multichannel signals [26], Multidimensional Iterative Filtering (MIF) for generic multidimensional datasets [4], and the Two-Dimensional Fast

Iterative Filtering (FIF2) algorithm for two-dimensional signal decomposition [27]. These generalizations inherit the core principles of FIF, adapting them to diverse spatial and temporal domains.

The FIF2 framework enables the decomposition of an n-dimensional signal $f \in \mathbb{R}^n$ into IMFs by approximating the high-dimensional moving average and iteratively removing it. In contrast to EMD, which relies on the identification of maxima and minima to define envelopes, FIF2 employs a convolution-based approach:

$$\mathcal{M}(f)(x) = \int_{\Omega} f(x+z)\, w(z)\, d^n z, \tag{2}$$

where $w : \mathbb{R}^n \to \mathbb{R}$ is a nonnegative, even, continuous filter function with compact support $\Omega \subset \mathbb{R}^n$, normalized so that $\int_{\Omega} w(z)\, d^n z = 1$.

For practical implementation, the algorithm assumes periodic boundary conditions. When such assumptions are incompatible with the signal, periodic extensions can be employed to mitigate boundary artifacts [28]. The support size Ω is chosen adaptively based on the signal's structural features, such as the distribution of extrema or the local frequency spectrum. This data-driven choice further contributes to the method's nonlinear and adaptive nature.

Algorithm 1 2D Fast Iterative Filtering IMFs = FIF2(f)

```
IMFs = {}
i=0
while there are oscillations left in f do
    i=i+1
    compute the filter support Ω̂ of the filter function w
    compute the 2D filter w
    compute DFT of signal f and of the filter w
    set k = 0
    while the stopping criterion is not satisfied do
        IMF^(i) = iDFT (I − diag (DFT(w)))^k DFT(f)
        k = k + 1
    end while
    IMFs = IMFs ∪ {IMF^(i)}
    f = f − IMF^(i)
end while
IMFs = IMFs ∪ {f}
```

The FIF2 method, see pseudocode in Algorithm 1 involves two nested loops:

- **Inner Loop:** Extracts an IMF by iteratively applying the filtering process until a stopping criterion is met.
- **Outer Loop:** Applies the same process to the residual signal, producing successive IMFs until the residual has at most one local extremum, classifying it as a trend signal.

The computational complexity of FIF2 is $\mathcal{O}(m \log m)$, where m is the maximum among all dimensions of the signal under investigation. The method's robustness and efficiency are enhanced by choosing a Generalized Fokker-Planck filter [4]. These filters are $C^{\infty}(\mathbb{R}^n)$, compactly supported, and widely used in applications. This method as been proven to be a priori convergent and stable [4, 3, 27].

In a future work we plan to apply this technique, as well as other methods like the Multivariate FIF [26], the Multidimensional and Multivariate FIF [5] to the analysis of the data sets listed above.

3. Conclusions

Waste management strategies play a pivotal role in determining the long-term sustainability of the sector, with direct implications for both environmental integrity and public health outcomes. Enhancing the sustainability of waste services requires strategic alignment with the Sustainable Development Goals (SDGs) and the guiding principles of European Union environmental policy. In this context, equipping policymakers with rigorous and comprehensive sustainability assessments is essential to inform the selection and implementation of the most effective and context-appropriate interventions at the local level.

Our previous empirical analysis demonstrates substantial heterogeneity in the sustainability of the waste sector across the territorial units under study [15], revealing a marked geographic divergence between Northern and Southern Italy. These spatial disparities underscore the critical need for integrating the SDGs and EU environmental directives into local waste governance frameworks, and for grounding policy interventions in robust, data-driven decision-support systems.

In this regard, the incorporation of non-stationary signal decomposition techniques—as applied in our case study— will offer a novel analytical lens for identifying priority areas and informing targeted interventions. These techniques facilitate the identification of latent temporal and spatial dynamics in waste management performance, thereby supporting more efficient and cost-effective policy design.

Furthermore, the application of these advanced methodologies will enable a deeper investigation into spatial correlations, convergence dynamics, and polarization phenomena in waste management outcomes. This, in turn, can provide valuable insights into the interplay between performance differentials and structural variables such as institutional frameworks, local economic conditions, and patterns of specialization in urban waste management systems.

To conclude, while our previous findings offer significant contributions to the understanding of territorial sustainability in waste services, further research is warranted to disentangle and quantitatively assess the influence of exogenous factors—including governance practices, regulatory environments, and socio-economic determinants—on complex policy decision-making processes within the sector. We plan to conduct these studies in a future work.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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