

Numerical modeling of IR SEDs of dusty CCSN within a Bayesian framework

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Abstract. We investigate the physical properties of dust in the environment of three core-collapse supernovae (CCSNe) through mid-infrared (mid-IR) spectral energy distribution (SED) modeling (both analytical and numerical methods) and interpret our results within a Bayesian framework. We provide evidence that the observed late-time mid-IR excess of the SNe can be described by dust models. We conclude that in case of various types of SNe, numerical dust models with a shell-like geometry can be reconciled with analytical models, regarding the essential properties of dust grains.

Keywords. supernovae: individual: SN 1980K, SN1993J, SN1996cr – infrared: stars

1. Introduction

Cosmic dust is one of the essential building blocks of the Universe. It originates from various sources, moreover, both theoretical expectations and observational results advocate that CCSNe are one of the main stellar sources of cosmic dust (for a review see e.g. [Sarangi et al. 2018](#)). Dust grains typically re-emit in the mid-IR and/or in the submillimeter regime. Thus, the mid-IR analysis of CCSNe provides an exceptional opportunity to reveal precious information about SN dust (e.g. [Szalai et al. 2019](#)).

We investigated the late-time mid-IR Spitzer data of SN 1980K ([Sugerman et al. 2012](#)), SN 1993J ([Zsíros et al. 2022](#)) and SN 1996cr (unpublished data). In order to have a fiducial understanding of the assumed dust properties, we fit a widely used analytical dust model adopted from [Hildebrand \(1983\)](#). The model describes the thermal emission of dust grains assuming a modified blackbody radiation from optically thin dust. We assumed a single dust composition – either amorphous carbon or silicate-type grains – in the models to fit the dust mass and temperatures ([Zsíros et al. 2022](#)).

We computed numerical models using the MOCASSIN (Monte Carlo SimulationS of Ionized Nebulae) radiative transfer code ([Ercolano et al. 2003; 2005; 2007](#)). The code follows the possible light-matter interactions and describes the re-emission by dust grains. We used a geometrical set-up with a central point source or a diffuse radiation field and a dust shell with a smooth density distribution. We applied a mixture of amorphous carbon and silicate dust.

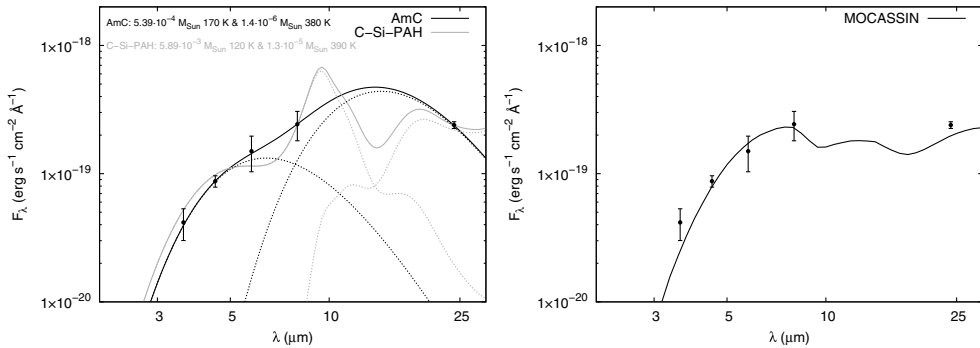


Figure 1. Our best-fit analytical dust models (left) with a numerical dust model (right) on mid-IR SED of SN 1980K (Sugerman *et al.* 2012).

Nevertheless, while numerical models provide more relevant representation of the possible physical background, they require a larger number of free parameters. Hence, we focused on the crucial parameters of the models. To have a deeper insight of the parameters, we interpreted our numerical models with a Bayesian inference method linked to a Markov Chain Monte Carlo (MCMC) algorithm (e.g. Bevan 2018, De Looze *et al.* 2019). For sampling, the method applies an affine invariant ensemble sampler (Goodman & Weare (2010)) implemented by an MCMC algorithm through the “emcee” package in *Python* (Foreman-Mackey *et al.* 2013). The sampling is executed by random walks of a selection of walkers, the posterior probabilities are drawn from the positions of the walkers, while the parameter ranges of the priors were determined from the respective numerical models.

We found that the observed late-time mid-IR emission can be described with dust models (see Fig. 1), thus supporting the presence of significant amounts of dust (in case of silicate dust: $\sim (1.4 - 5.9) \cdot 10^{-3} M_{\odot}$) in the vicinity of all three SNe in accordance with previous studies (e.g. Niculescu-Duvaz *et al.* (2022)).

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