



$\tau_{\text{ext}}(\lambda) = \int_0^{\infty} \pi r^2 Q_{\text{ext}}(r, \lambda, \eta) n(r) dr$  (1929),  $\tau_{\text{scat}}(\lambda) = \int_0^{\infty} \pi r^2 Q_{\text{scat}}(r, \lambda, \eta) n(r) dr$ ,  $\tau_{\text{abs}}(\lambda) = \tau_{\text{ext}}(\lambda) - \tau_{\text{scat}}(\lambda)$ ,  $\tau_{\text{ext}}(\lambda) = \beta \lambda^{-\alpha}$ ,  $\tau_{\text{scat}}(\lambda) = \beta_{\text{scat}} \lambda^{-\alpha_{\text{scat}}}$ ,  $\tau_{\text{abs}}(\lambda) = \beta_{\text{abs}} \lambda^{-\alpha_{\text{abs}}}$ .

$$\tau_{\text{ext}}(\lambda) = \int_0^{\infty} \pi r^2 Q_{\text{ext}}(r, \lambda, \eta) n(r) dr + q(\lambda), \tag{1}$$

$r$  is the radius of the particle;  $n(r)$  is the number concentration of particles of radius  $r$ ;  $Q_{\text{ext}}(r, \lambda, \eta)$  is the extinction efficiency factor;  $q(\lambda)$  is the scattering cross-section of the particle;  $Q_{\text{scat}}(r, \lambda, \eta)$  is the scattering efficiency factor;  $Q_{\text{abs}}(r, \lambda, \eta) = Q_{\text{ext}}(r, \lambda, \eta) - Q_{\text{scat}}(r, \lambda, \eta)$  is the absorption efficiency factor;  $\eta$  is the refractive index of the particle;  $\lambda$  is the wavelength of the incident radiation;  $\beta$ ,  $\beta_{\text{scat}}$ ,  $\beta_{\text{abs}}$ ,  $\alpha$ ,  $\alpha_{\text{scat}}$ ,  $\alpha_{\text{abs}}$  are the parameters of the power-law model.

The power-law model has been widely used in the literature (e.g., Tegen et al., 1997; Wang et al., 2001; Wang & Tegen, 2002; Wang et al., 2003; Wang & Tegen, 2004; Wang et al., 2005; Wang & Tegen, 2006; Wang et al., 2007; Wang & Tegen, 2007; Wang et al., 2008; Wang & Tegen, 2008; Wang et al., 2009; Wang & Tegen, 2009; Wang et al., 2010; Wang & Tegen, 2010; Wang et al., 2011; Wang & Tegen, 2011; Wang et al., 2012; Wang & Tegen, 2012; Wang et al., 2013; Wang & Tegen, 2013; Wang et al., 2014; Wang & Tegen, 2014; Wang et al., 2015; Wang & Tegen, 2015; Wang et al., 2016; Wang & Tegen, 2016; Wang et al., 2017; Wang & Tegen, 2017; Wang et al., 2018; Wang & Tegen, 2018; Wang et al., 2019; Wang & Tegen, 2019; Wang et al., 2020; Wang & Tegen, 2020; Wang et al., 2021; Wang & Tegen, 2021; Wang et al., 2022; Wang & Tegen, 2022; Wang et al., 2023; Wang & Tegen, 2023; Wang et al., 2024; Wang & Tegen, 2024; Wang et al., 2025; Wang & Tegen, 2025).

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$$\int_a^b k(x, y)n(y) dy = o(x), \quad (1)$$

### 3. Problem formulation

#### 3.1. Operator equations of the first kind

(Knutson & Seinfeld, 1989; Seinfeld & Pandis, 1996; Pandis & Seinfeld, 1995; Seinfeld & Pandis, 2000; Wang et al., 2007)

$$\int_a^b k(x, y)n(y) dy = o(x), \quad (2)$$

where  $x \in [a, b]$ ,  $k(x, y) = k(x, y, \tau)$  is the kernel function,  $n(x)$  is the unknown function,  $H$  is the Hilbert space,  $o(x)$  is the source term.

$$\int_a^b k(x, y)n(y) dy + q(x) = o(x) + q(x) = d(x), \quad (3)$$

where  $q(x)$  is the regularization function,  $n(x)$  is the unknown function,  $d(x)$  is the source term.

$$K : F \rightarrow O, \quad (Kn)(\lambda) + q(\lambda) = d(\lambda), \quad (4)$$

where  $(Kn)(\lambda) := \int_0^\infty k(r, \lambda, \eta)n(r) dr$ ;  $k(r, \lambda, \eta) = \pi r^2 Q(r, \lambda, \eta)$ ;  $F$  is the Hilbert space,  $O$  is the Hilbert space,  $d(\lambda)$  is the source term.

$$Kn + q = d. \quad (5)$$

#### 3.2. Discrete formulation in finite spaces

(Seinfeld & Pandis, 2006), where  $n(r)$  is approximated by  $\{r_j\}_{j=1}^N$ .

$$\mathcal{H} = (\mathcal{H}_{ij})_{M \times N}, \vec{n}, \vec{q}, \vec{d} \in \mathbb{R}^M, \quad \mathcal{H}\vec{n} + \vec{q} = \vec{d}. \quad (6)$$

4. Theoretical development

4.1. Solving for an efficient a priori information in  $l^1$  space

$$\min_{\vec{n}} \|\vec{n}\|_{l^1} \quad \text{subject to} \quad \mathcal{H}\vec{n} = \vec{d}, \quad \vec{n} \geq 0, \quad (4)$$

where  $\vec{n}$  is the vector of unknowns,  $\mathcal{H}$  is the matrix of the forward model,  $\vec{d}$  is the vector of observed data, and  $\vec{0}$  is the zero vector. (2003)

where  $\vec{0}$  is the zero vector,  $\mathcal{H}$  is the matrix of the forward model,  $\vec{d}$  is the vector of observed data, and  $\vec{0}$  is the zero vector.

$$\min_{\vec{n}} \|\vec{n}\|_{l^1} \quad \text{subject to} \quad \mathcal{H}\vec{n} = \vec{d}, \quad \vec{n} \geq 0. \quad (7)$$

$$\min_{\vec{n}} \|\vec{n}\|_{l^1} \quad \text{subject to} \quad \mathcal{H}\vec{n} = \vec{d}, \quad \vec{n} \geq 0, \quad (8)$$

$$\min_{\vec{n}} \|\vec{n}\|_{l^1} \quad \text{subject to} \quad \mathcal{H}\vec{n} = \vec{d}, \quad \vec{n} \geq 0. \quad (8)$$

$$S = \{\vec{n} : \mathcal{H}\vec{n} = \vec{d}, \vec{n} \geq 0\}. \quad (8)$$

$$\vec{d} - \mathcal{H}\vec{z} = \vec{s}, \quad \vec{s} \geq 0. \quad (9)$$

$$\begin{aligned} \mathcal{H}\vec{n} &= \vec{d}, & (10) \\ \mathcal{H}\vec{z} + \vec{s} &= \vec{e}, & (11) \\ \tilde{S}\tilde{F}\vec{e} &= 0, & (12) \\ \vec{n} \geq 0, \quad \vec{s} &\geq 0, & (13) \end{aligned}$$

$$\tilde{S} = \begin{pmatrix} s_1 & s_2 & \dots & s_N \end{pmatrix}, \quad \tilde{F} = \begin{pmatrix} n_1 & n_2 & \dots & n_N \end{pmatrix}.$$

$$\min_{\{\vec{n}_k, \vec{z}_k, s_k\}} \|\vec{d} - \mathcal{H}\vec{n}_k\| + \|\mathcal{H}\vec{z}_k + s_k - \vec{e}\| \quad \text{subject to} \quad \vec{n}_k > 0, \quad s_k > 0. \quad k$$

$$\beta_k \in [0, 1], \quad (10) \text{--}(12).$$

$$[\Delta \vec{n}, \Delta \vec{z}, \Delta s] \begin{bmatrix} \mathcal{K} & 0 & 0 \\ 0 & \mathcal{K} & I \\ \tilde{S}_k & 0 & \tilde{F}_k \end{bmatrix} \begin{bmatrix} \Delta \vec{n} \\ \Delta \vec{z} \\ \Delta s \end{bmatrix} = \begin{bmatrix} \vec{d} - \mathcal{K} \vec{n}_k \\ e - \mathcal{K} \vec{z}_k - s_k \\ \beta_k \mu_k e - \tilde{S}_k \tilde{F}_k e \end{bmatrix}, \tag{14}$$

$$\beta_k = (1/N) \vec{n}_k s_k, \quad \tau_k = \beta_k \mu_k, \quad \vec{n}_{k+1} := \vec{n}_k + \tau_k \Delta \vec{n}, \quad \vec{z}_{k+1} := \vec{z}_k + \tau_k \Delta \vec{z}, \quad s_{k+1} := s_k + \tau_k \Delta s, \tag{15}$$

$\vec{n}_0, \vec{z}_0, s_0$  a priori

4.2. Damped Gauss–Newton method

$$R(\vec{n}) = \mathcal{K} \vec{n} - \vec{d}, \quad J[\vec{n}] = \frac{\partial R(\vec{n})}{\partial \vec{n}}, \quad J[\vec{n}]^T J[\vec{n}] = H, \tag{16}$$

$$g(\vec{n}) = \mathcal{K} (\mathcal{K} \vec{n} - \vec{d}), \quad H = \mathcal{K}^T \mathcal{K}, \tag{17}$$

$$s_k = \vec{n}_{k+1} - \vec{n}_k, \quad \frac{1}{2} \|R(\vec{n}_k) + R'(\vec{n}_k) s\|^2, \tag{18}$$

$$s_k = -R'(\vec{n}_k) g_k = -H^{-1} g_k, \tag{19}$$

$$\vec{n}_{k+1} = \vec{n}_k + s_k, \tag{20}$$

$$g_k = g(\vec{n}_k).$$

$$s_k = -\gamma_k H^{-1} g_k, \tag{21}$$

$$\gamma_k = \arg \min_{\gamma} \phi(\gamma) := J[\vec{n}_k + \gamma s_k]. \tag{22}$$

$H$  is symmetric positive definite (SPD) matrix.  $\vec{f}_k$  is the  $k$ th iteration of the Gauss–Newton method.  $\vec{f}_k$  is the  $k$ th iteration of the Gauss–Newton method.

4.3. Regularization by incorporating an efficient a priori information

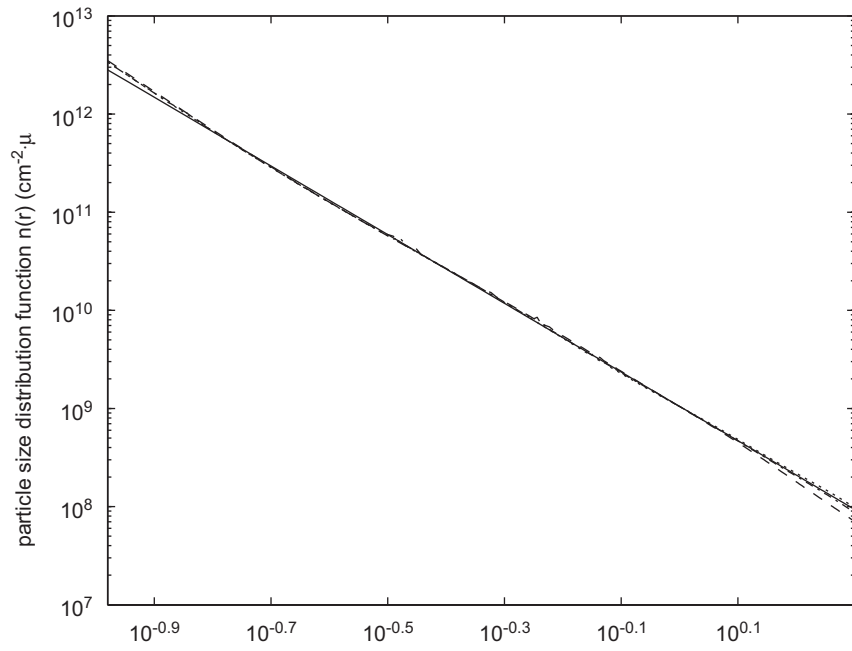
$$s_k = -\gamma_k (H + \alpha_k L)^{-1} g_k, \tag{23}$$

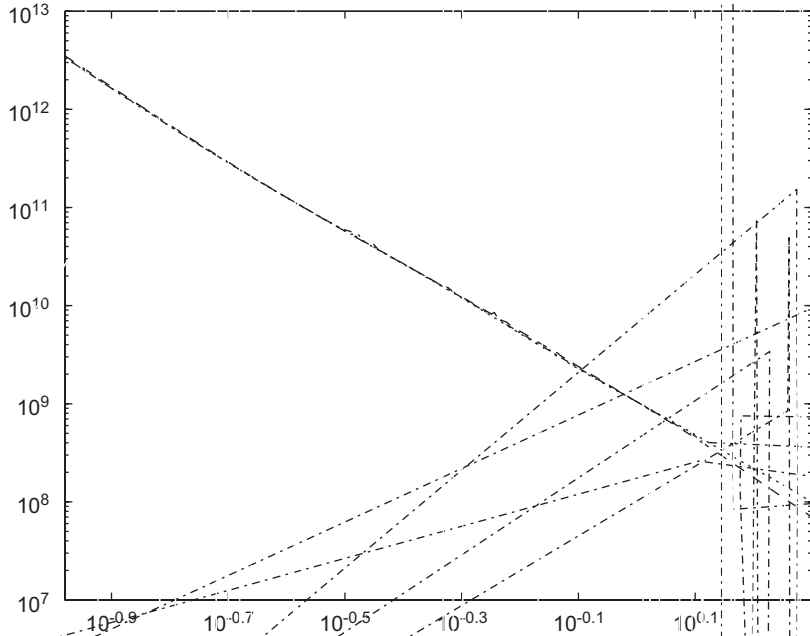
$L$  is a SPD matrix,  $\alpha_k$  is a regularization parameter.  $\vec{f}_k$  is the  $k$ th iteration of the Gauss–Newton method.  $\vec{f}_k$  is the  $k$ th iteration of the Gauss–Newton method.

$$s_k = -\gamma_k (H + \alpha_k L)^{-1} (g_k + \alpha_k (\vec{n}_k - \vec{n}_0)), \tag{24}$$

$\vec{n}_0$  is a priori information.  $\vec{n}$  is the solution of the inverse problem. (1994).







$-2, \mu\text{m}^{-1}$

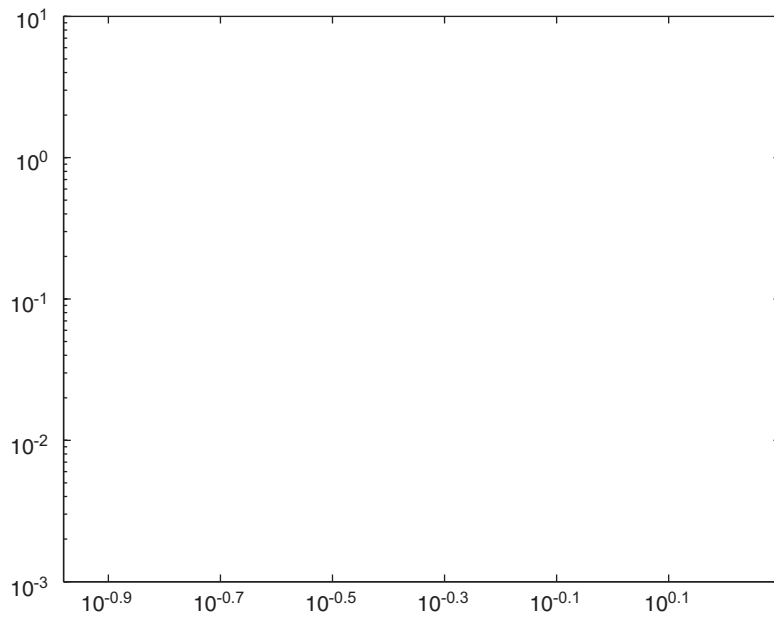


Table 1

Imaginary part	$\eta = 1.45 - 0.00i$	$\eta = 1.45 - 0.03i$	$\eta = 1.50 - 0.02i$
$\delta = 0.005$	$1.6443 \times 10^{-4}$	$1.2587 \times 10^{-4}$	$2.2773 \times 10^{-4}$
$\delta = 0.01$	$1.6493 \times 10^{-4}$	$1.2720 \times 10^{-4}$	$2.2847 \times 10^{-4}$
$\delta = 0.05$	$1.6996 \times 10^{-4}$	$1.3938 \times 10^{-4}$	$2.3504 \times 10^{-4}$

Table 2

Imaginary part	$\eta = 1.45 - 0.00i$	$\eta = 1.45 - 0.03i$	$\eta = 1.50 - 0.02i$
$\delta = 0.005$	17	13	16
$\delta = 0.01$	17	13	16
$\delta = 0.05$	17	13	16



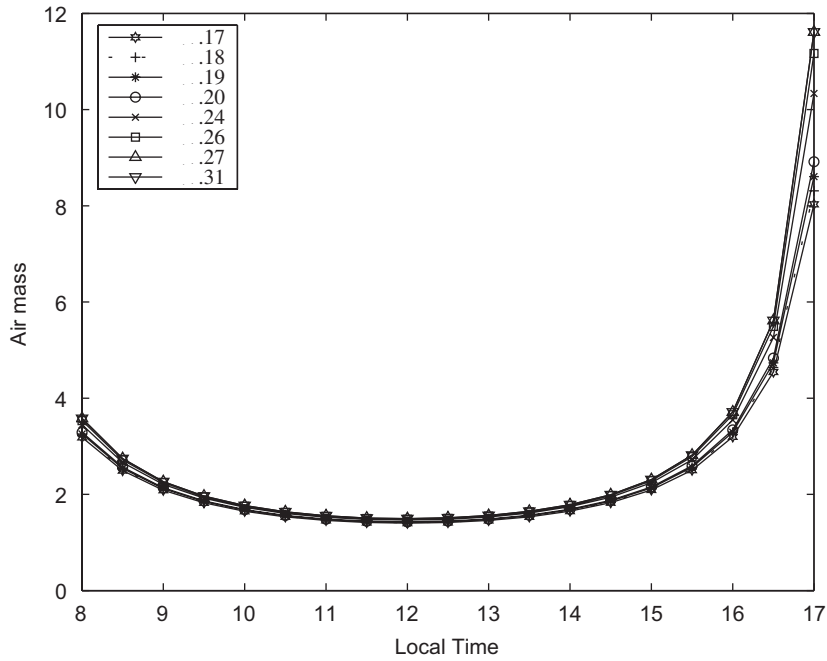


Fig. 5. Air mass versus local time for 17, 20, 24, 26, 27, 31, 2005.

Fig. 6. Air mass versus local time for 17, 20, 24, 26, 27, 31, 2005.

The air mass profiles for 17, 20, 24, 26, 27, 31, 2005 are shown in Fig. 6. The air mass profiles for 17, 20, 24, 26, 27, 31, 2005 are shown in Fig. 6. The air mass profiles for 17, 20, 24, 26, 27, 31, 2005 are shown in Fig. 6.

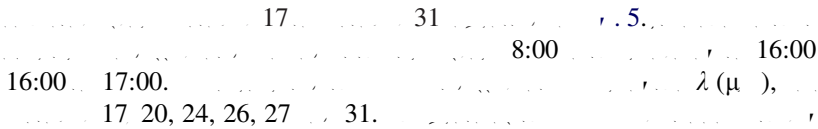


Fig. 6. Air mass versus local time for 17, 20, 24, 26, 27, 31, 2005.

The air mass profiles for 17, 20, 24, 26, 27, 31, 2005 are shown in Fig. 6. The air mass profiles for 17, 20, 24, 26, 27, 31, 2005 are shown in Fig. 6. The air mass profiles for 17, 20, 24, 26, 27, 31, 2005 are shown in Fig. 6.

$\eta = 1.50 - 0.095i$

H (1980), J (1963), H (1994), M (1994), H (1994),  $\alpha_0$  (1994), 0.1.

( & , 1977; , 2003),  $\alpha_k$  (1994),  $\alpha_k^*$  (1994),  $\alpha_k^*$  (1994).

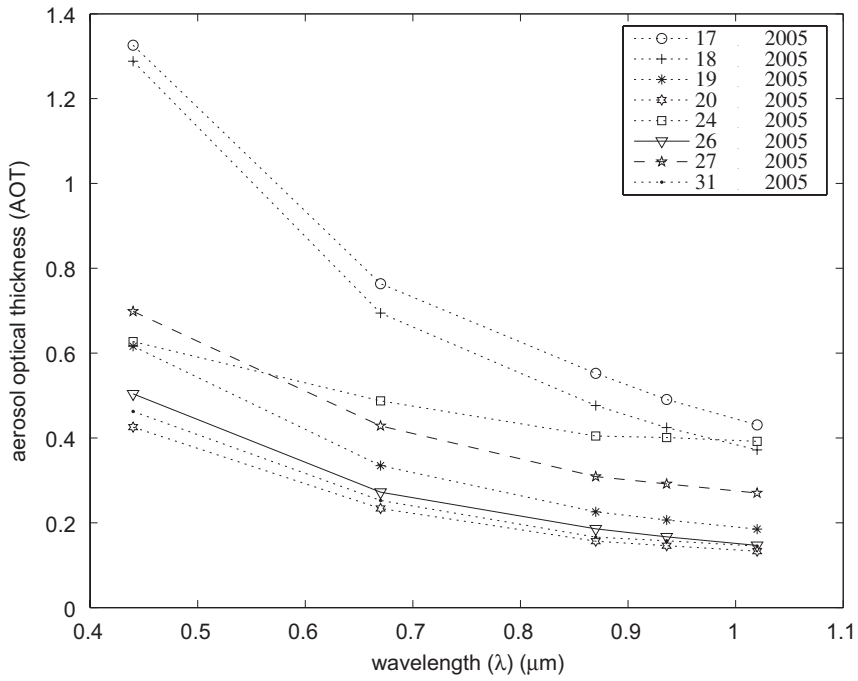


Fig. 6. Aerosol optical thickness (AOT) versus wavelength ( $\lambda$ ) in  $\mu\text{m}$  for various dates in 2005.

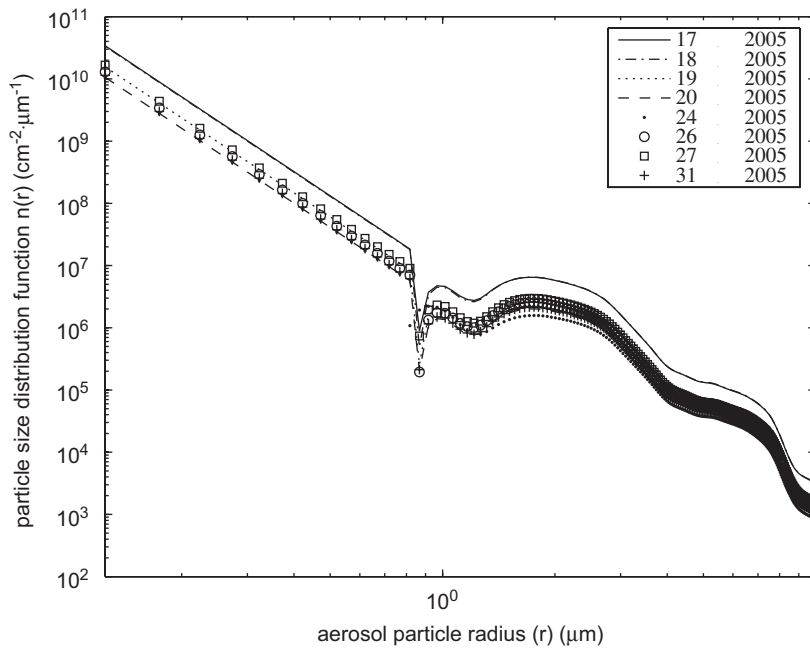


Fig. 7. Particle size distribution function  $n(r)$  in  $\text{cm}^{-2}\mu\text{m}^{-1}$  versus aerosol particle radius ( $r$ ) in  $\mu\text{m}$  for various dates in 2005.

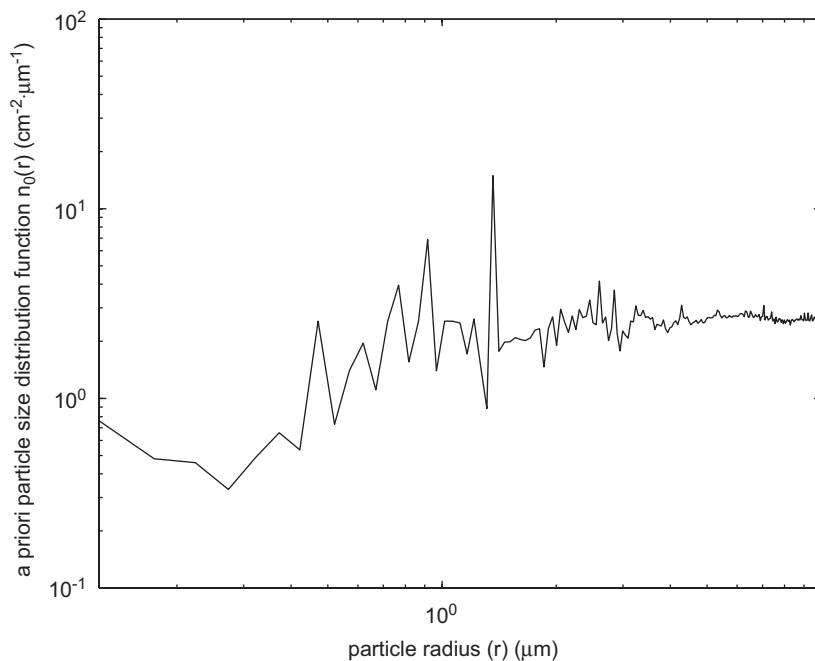


Fig. 8. A priori particle size distribution function  $n_0$  (M), 2005.

...  $1.0 \mu$  ...  $1.0 \mu$  , ...  
*a priori* ...  $\vec{n}_0$ , ... Fig. 8 ...  $\vec{n}_0$  ... 11. ...



..., *a priori* : (1) ...,  $n_0$  ...,  $l^1$  ...,  $l^1$  ...; (2) ...,  $l^2$  ...

**Appendix C. Computing an *a priori* by searching for an interior point solution**

*a priori* ...,  $n_0$  ...,  $l^1$  ...,  $l^1$  ...  
 4.1  
 $c \vec{n} \dots \mathcal{H} \vec{n} = \vec{d}, \vec{n} \geq 0,$  ( .1)

$\vec{n} \dots N \dots$  ( .1)  
 $\vec{d} \vec{z} \dots \mathcal{H} \vec{z} + s = c, s \geq 0.$  ( .2)

..., ...,  $\mu$ :  
 $c \vec{n} - \mu \sum_{j=1}^N \dots (n_j) \dots \mathcal{H} \vec{n} = \vec{d}, \vec{n} \geq 0.$  ( .3)

fi  
 $\vec{n}_j \rightarrow 0 \dots -\mu \dots (n_j) = \infty.$  ( .4)

$\vec{n} > 0 \dots, \dots \vec{n} > 0.$  fi  
 $L(\vec{n}, \vec{z}) = c \vec{n} - \mu \sum_{j=1}^N \dots (n_j) - \vec{z} (\mathcal{H} \vec{n} - \vec{d}).$  ( .5)

$\frac{\partial L}{\partial n_j} = c_j - \mu n_j^{-1} - \mathcal{H}_{:j} \vec{z}, \quad \frac{\partial L}{\partial z_i} = \vec{d}_i - \mathcal{H}_{i:} \vec{n},$  ( .6)  
 $\mathcal{H}_{:j} \dots j \dots \mathcal{H}, \mathcal{H}_{i:} \dots i \dots \mathcal{H}.$

$\vec{n} L(\vec{n}, \vec{z}) = c - \mu D^{-1} e - \mathcal{H} \vec{z}, \quad \vec{z} L(\vec{n}, \vec{z}) = \vec{d} - \mathcal{H} \vec{n},$  ( .7)

$D = \begin{bmatrix} n_1 & 0 & \dots & 0 \\ 0 & n_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & n_N \end{bmatrix}.$  ( .8)

$\mathcal{H} \vec{z} = c - \mu D^{-1} e, \quad \mathcal{H} \vec{n} = \vec{d}, \quad \vec{n} > 0.$  ( .9)

fi  $s = \mu D^{-1} e,$   
 $\mathcal{H} \vec{z} + s = c, \quad \mathcal{H} \vec{n} = \vec{d}, \quad Ds = \mu e, \quad \vec{n} > 0.$  ( .10)

$(\vec{n}, \vec{z}, s) \dots, \dots, \vec{n} \in S_p = \{\vec{n} : \mathcal{H} \vec{n} = \vec{d}, \vec{n} > 0\}$  ...,  
 $(\vec{z}, s) \in S_D = \{(\vec{z}, s) : \mathcal{H} \vec{z} + s = c, s = \mu D^{-1} e > 0\}.$

$$F(\vec{n}, \vec{z}, s) = \begin{bmatrix} \mathcal{H}\vec{n} - \vec{d} \\ \mathcal{H}\vec{z} + s - c \\ Ds - \beta\mu e \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \tag{.11}$$

$\beta \in (0, 1)$ . For any  $(\vec{n}_k, \vec{z}_k, s_k) \in \mathbb{R}^3_+$ ,  $F(\vec{n}, \vec{z}, s) = 0$  if and only if

$$F(\vec{n}_k, \vec{z}_k, s_k) \begin{bmatrix} d_{\vec{n}} \\ d_{\vec{z}} \\ d_s \end{bmatrix} = -F(\vec{n}_k, \vec{z}_k, s_k). \tag{.12}$$

Therefore,  $F(\vec{n}_k, \vec{z}_k, s_k) = \begin{bmatrix} \mathcal{H} & 0 & 0 \\ 0 & \mathcal{H} & I \\ S_k & 0 & D_k \end{bmatrix}$ , ( .13)

$$\begin{bmatrix} \mathcal{H} & 0 & 0 \\ 0 & \mathcal{H} & I \\ S_k & 0 & D_k \end{bmatrix} \begin{bmatrix} d_{\vec{n}} \\ d_{\vec{z}} \\ d_s \end{bmatrix} = \begin{bmatrix} \vec{d} - \mathcal{H}\vec{n}_k \\ c - \mathcal{H}\vec{z}_k - s_k \\ -D_k s_k + \beta\mu_k e \end{bmatrix}. \tag{.14}$$

**Algorithm** (Computing an interior point solution).

- (1) Choose  $(\vec{n}_1, \vec{z}_1, s_1) \in \mathbb{R}^3_+$  with  $\vec{n}_1, \vec{z}_1 > 0$ , and  $\varepsilon_{\vec{n}}, \varepsilon_{\vec{z}}, \varepsilon_s > 0$ ;
- (2) Set  $k := 1$ ;  $k \leq \infty$ ;
- (3) Compute

$$r_{\vec{n}}^k = \vec{d} - \mathcal{H}\vec{n}_k,$$

$$r_{\vec{z}}^k = c - \mathcal{H}\vec{z}_k - s_k,$$

$$\mu_k = \frac{1}{N} \vec{n}_k s_k;$$

- (4) If  $\|r_{\vec{n}}^k\| \leq \varepsilon_{\vec{n}}, \|r_{\vec{z}}^k\| \leq \varepsilon_{\vec{z}}, \|\mu_k\| \leq \varepsilon_s$ , stop;
- (5) Choose  $\beta \in (0, 1)$  and solve ( .14);
- (6) Compute

$$\tau = \min \left\{ \tau \geq 0 \left\{ \begin{bmatrix} \vec{n}_k \\ s_k \end{bmatrix} + \tau \begin{bmatrix} d_{\vec{n}} \\ d_s \end{bmatrix} \geq 0 \right\} \right\}; \tag{.15}$$

- (7) Choose  $\theta \in (0, 1)$ , and set
- $\tau := \min \{ \theta\tau, 1 \}$ ;

- (8) Compute
- $\vec{n}_{k+1} := \vec{n}_k + \tau d_{\vec{n}}$ ,
- $\vec{z}_{k+1} := \vec{z}_k + \tau d_{\vec{z}}$ ,
- $s_{k+1} := s_k + \tau d_s$ .

**Example (Computing an interior point solution).**

$$-1n_1 - 2n_2, \quad n_1 + n_2 = 1, \quad n_1, n_2 \geq 0. \tag{.16}$$

$$\vec{n} = [n_1 \ n_2], \quad c = [-1 \ -2], \quad \mathcal{K} = [1 \ 1], \quad \vec{d} = 1,$$

$$F(\vec{n}, \vec{z}, s) = \begin{bmatrix} \mathcal{K}\vec{n} - \vec{d} \\ \mathcal{K}\vec{z} + s - c \\ Ds - \beta\mu e \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \tag{.17}$$

$$\vec{z} = [z_1 \ z_2], \quad s = [s_1 \ s_2], \quad D = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}, \quad \mu = \frac{1}{2}\vec{n} \cdot s, \quad e = [1 \ 1], \quad \beta = 0.1 \in [0, 1].$$

$$F(\vec{n}_k, \vec{z}_k, s_k) = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ s_1 & 0 & 0 & \vec{n}_1 & 0 \\ 0 & s_2 & 0 & 0 & \vec{n}_2 \end{bmatrix}.$$

$$\vec{n}^* = [0.0000 \ 1.0000], \quad s \vec{n}^* = 1.0042e - 007, \quad c \vec{n}^* = -2.0000.$$

**Appendix D. Damped Gauss–Newton method with line search**

$$J[\vec{n}] := \frac{1}{2} \|R(\vec{n})\|^2. \tag{.1}$$

$$s_k = \vec{n}_{k+1} - \vec{n}_k$$

$$\frac{1}{2} \|R(\vec{n}_k) + R'(\vec{n}_k)s\|^2, \tag{.2}$$

$$s_k = -H^{-1}g_k, \quad \vec{n}_{k+1} = \vec{n}_k + s_k.$$

(Moré & Moré, 1999),  $\vec{n}_k$  is the current point,  $\gamma_k$  is the step size,

$$s_k = -\gamma_k H^{-1}g_k. \tag{.3}$$

The step size  $\gamma_k$  is chosen such that  $J(\vec{n}_k + \gamma_k s_k) \leq J(\vec{n}_k) + c_1 \gamma_k g_k \cdot s_k$ , where  $J$  is the objective function,  $g_k$  is the gradient of  $J$  at  $\vec{n}_k$ , and  $H$  is the Hessian of  $J$  at  $\vec{n}_k$ .

$$J(\vec{n}_k + \gamma_k s_k) \leq J(\vec{n}_k) + c_1 \gamma_k g_k \cdot s_k, \tag{.4}$$

$$c_1 \in (0, 1).$$

The step size  $\gamma_k$  is chosen such that  $g(\vec{n}_k + \gamma_k s_k) \cdot s_k \geq c_2 g_k \cdot s_k$ , where  $g$  is the gradient of  $J$  at  $\vec{n}_k + \gamma_k s_k$ .

$$g(\vec{n}_k + \gamma_k s_k) \cdot s_k \geq c_2 g_k \cdot s_k, \tag{.5}$$

$$c_2 \in (c_1, 1), \quad c_1 < c_2. \tag{.4}$$

$$(4) \text{ (5)} \quad c_1 = 0.1, \quad c_2 = 0.4.$$



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