

# Rounding and Uncertainties in Determining Parameters and Properties from Fits to Experimental Data

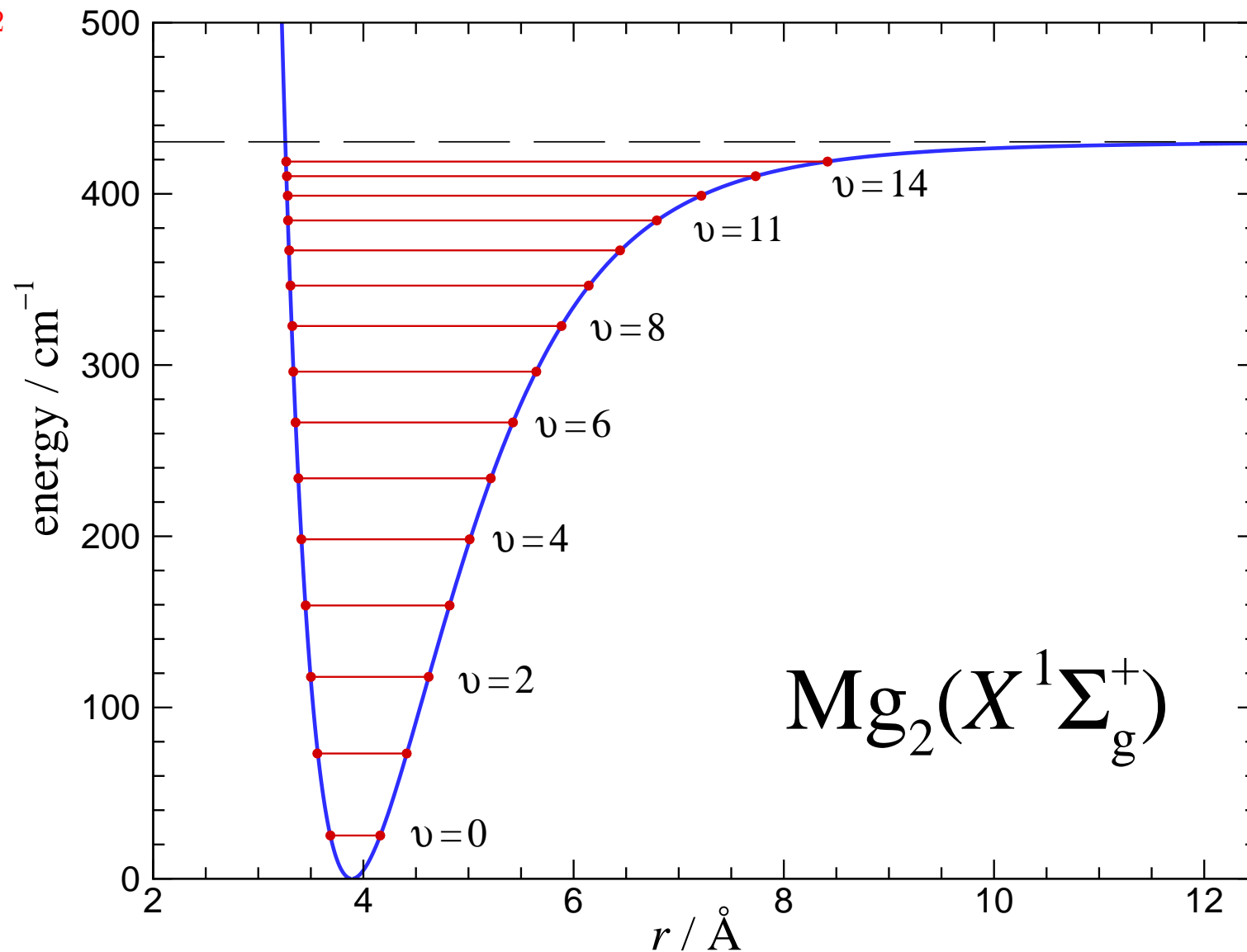
*or*

## A Failure to Round Data-Analysis Parameters Appropriately May Make them Useless!

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Consider a recent analysis of extensive high-quality data for the ground state of  $\text{Mg}_2$



A direct fit to 4741 data with accuracies in the range  $0.005 - 0.05 \text{ cm}^{-1}$  yielded an analytic potential defined by the parameters ...

**Table I.** Parameters of “X-representation” potential energy function from fit to  $\text{Mg}_2(X^1\Sigma_g^+)$  data.<sup>a</sup>

$$V(r) = \sum_{i=1}^n a_i \xi(r)^i \quad \text{with} \quad \xi(r) = \frac{r - R_m}{r + b R_m}$$

parameter	
$R_m$	[3.89039]
$a_1$	$-0.770548964164001222 \times 10^{-2}$
$a_2$	$0.705289125191954554 \times 10^4$
$a_3$	$-0.179327568767261764 \times 10^5$
$a_4$	$0.228278059421389626 \times 10^5$
$a_5$	$-0.144881409083685430 \times 10^5$
$a_6$	$-0.638841357804591826 \times 10^5$
$a_7$	$0.201722011755478365 \times 10^6$
$a_8$	$-0.286947115902508434 \times 10^6$
$a_9$	$0.528096212291666190 \times 10^6$
$a_{10}$	$-0.841629359994647559 \times 10^6$
$a_{11}$	$0.510277917592615297 \times 10^6$
$\overline{dd}$	1.46224

*is the dimensionless RMS Deviation*  
 $\equiv \frac{1}{N} \sum_{i=1}^N \left( \frac{y_i^{\text{calc}} - y_i^{\text{obs}}}{\text{unc}(y_i)} \right)^2$

<sup>a</sup> H. Knöckel and S. Rühmann and E. Tiemann, *J. Chem. Phys.* **138**, 94303 (2013).

**Table I.** Parameters of “X-representation” potential energy function from fit to  $\text{Mg}_2(X^1\Sigma_g^+)$  data.<sup>a</sup>

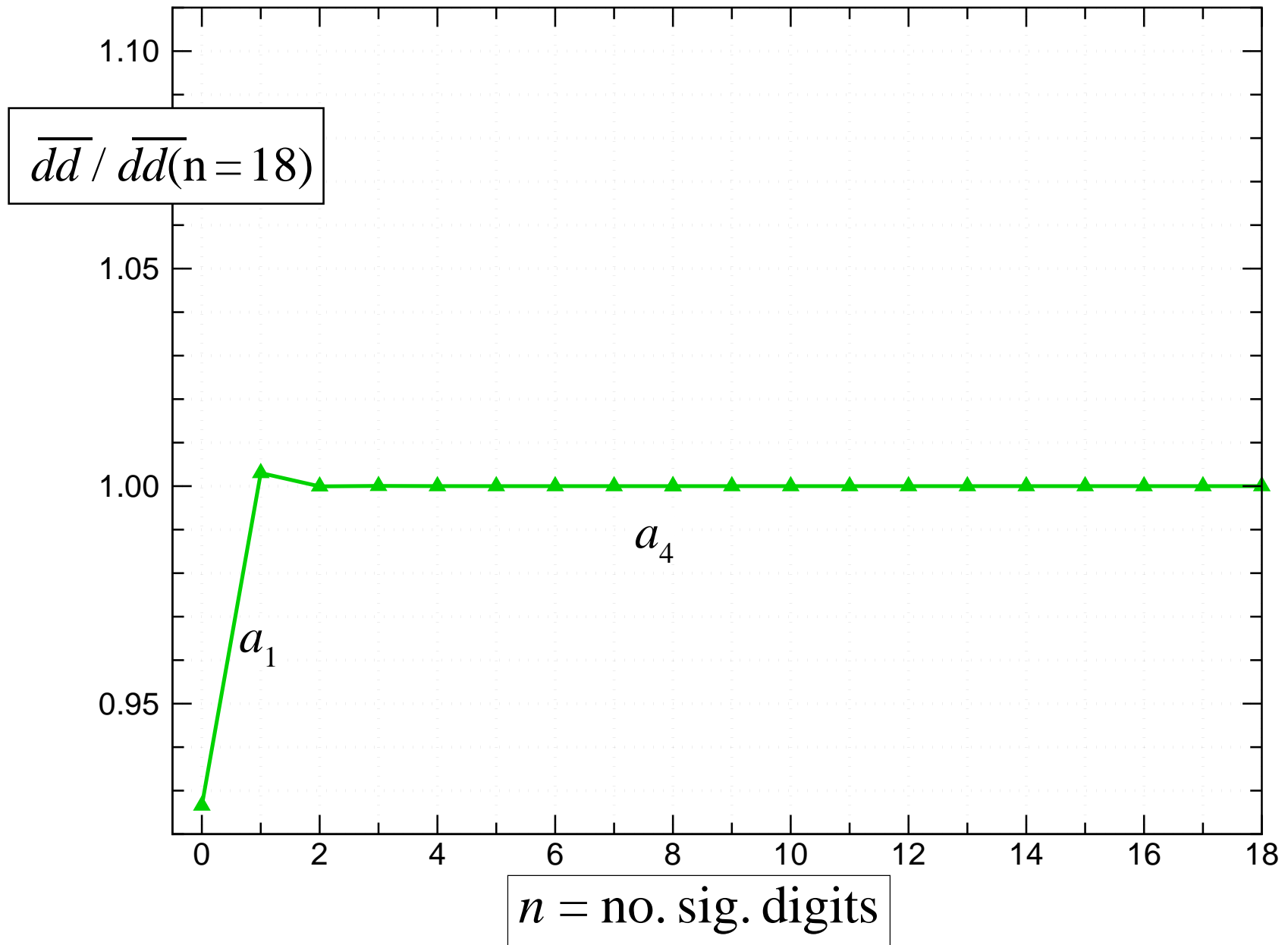
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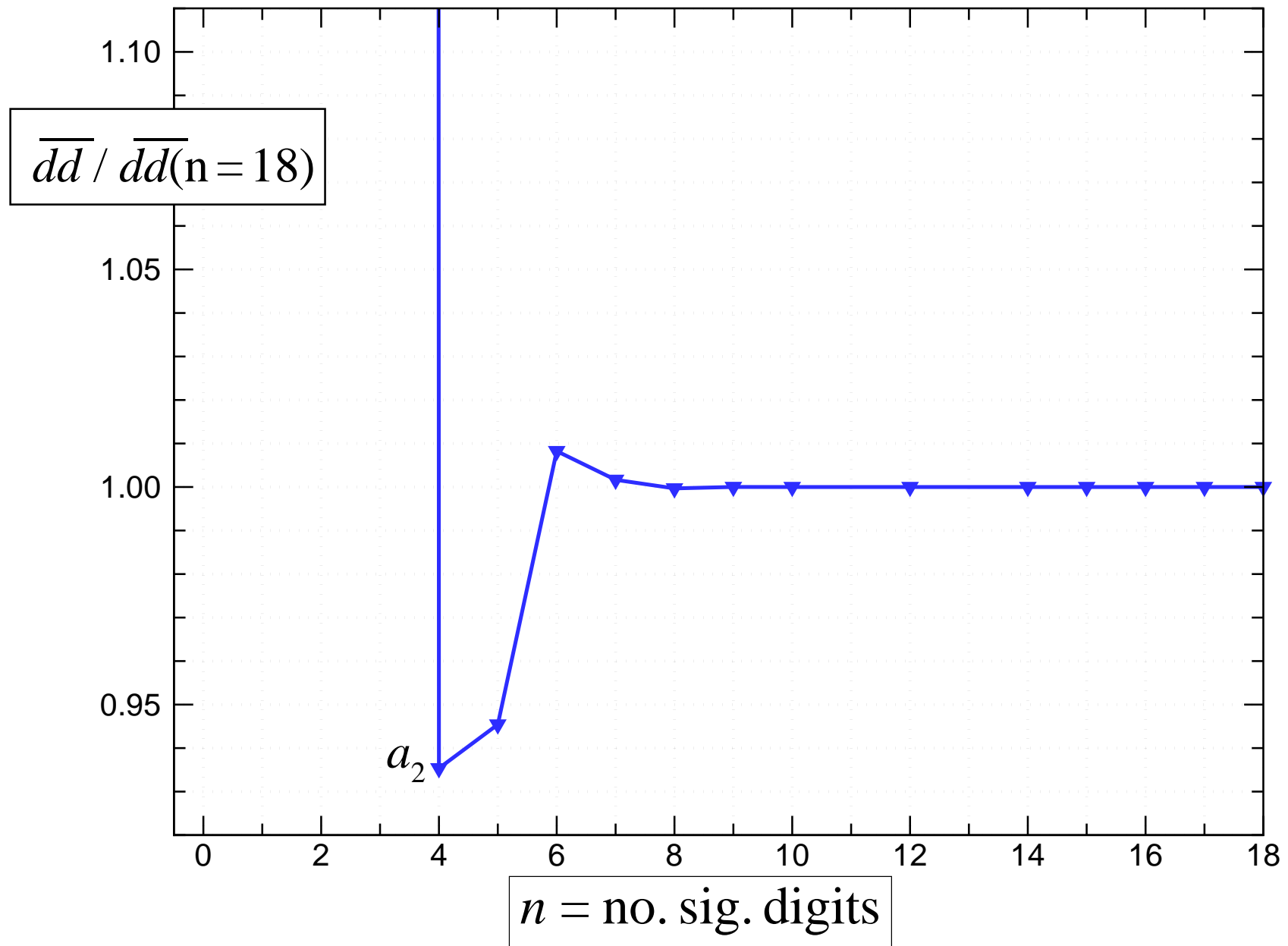
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But 18 digits is an awful lot! *Can we round them off in a sensible way?*

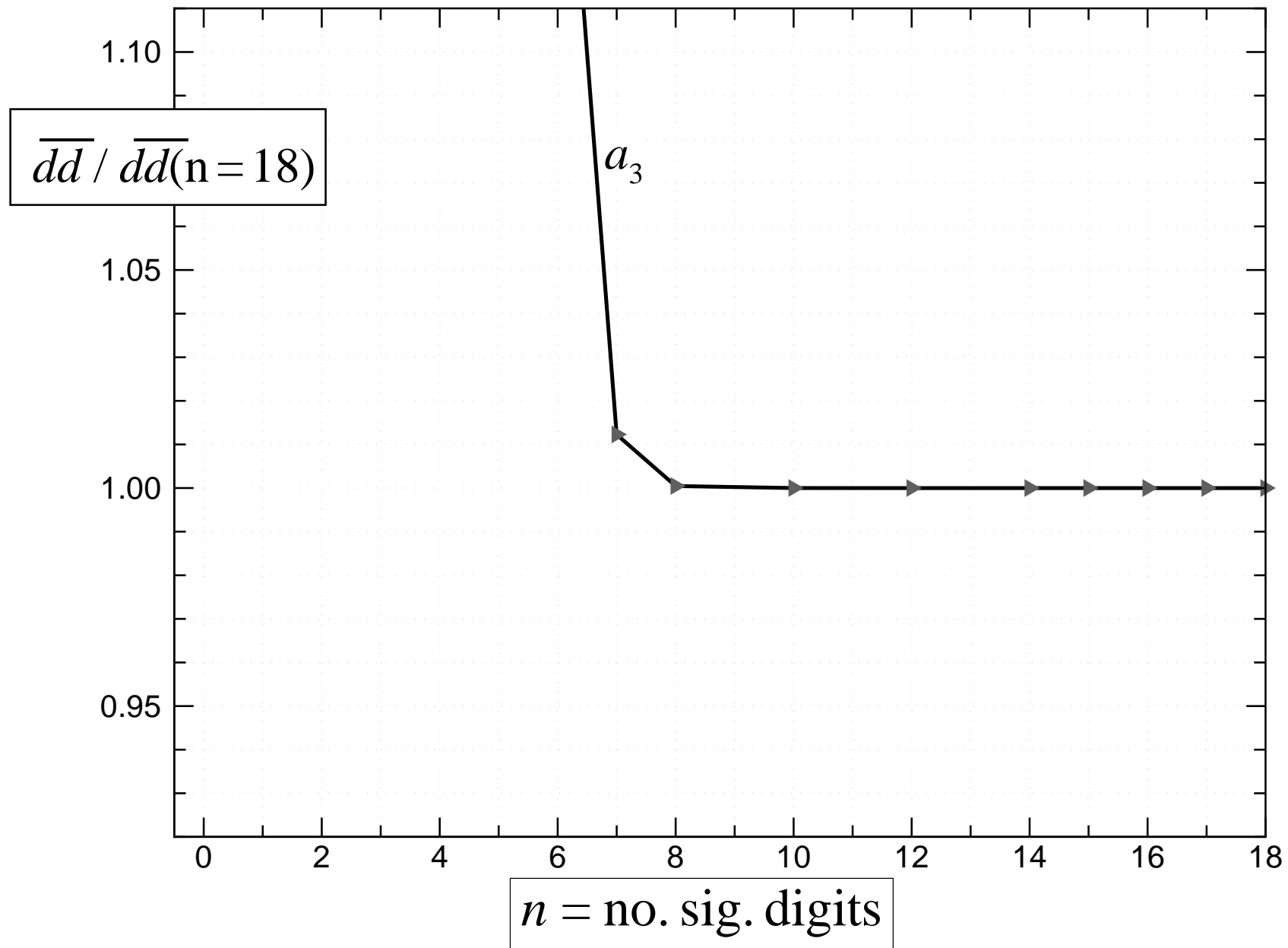
What happens to  $\overline{dd}$  if we round parameter  $a_1$  at its  $n^{\text{th}}$  significant digit?



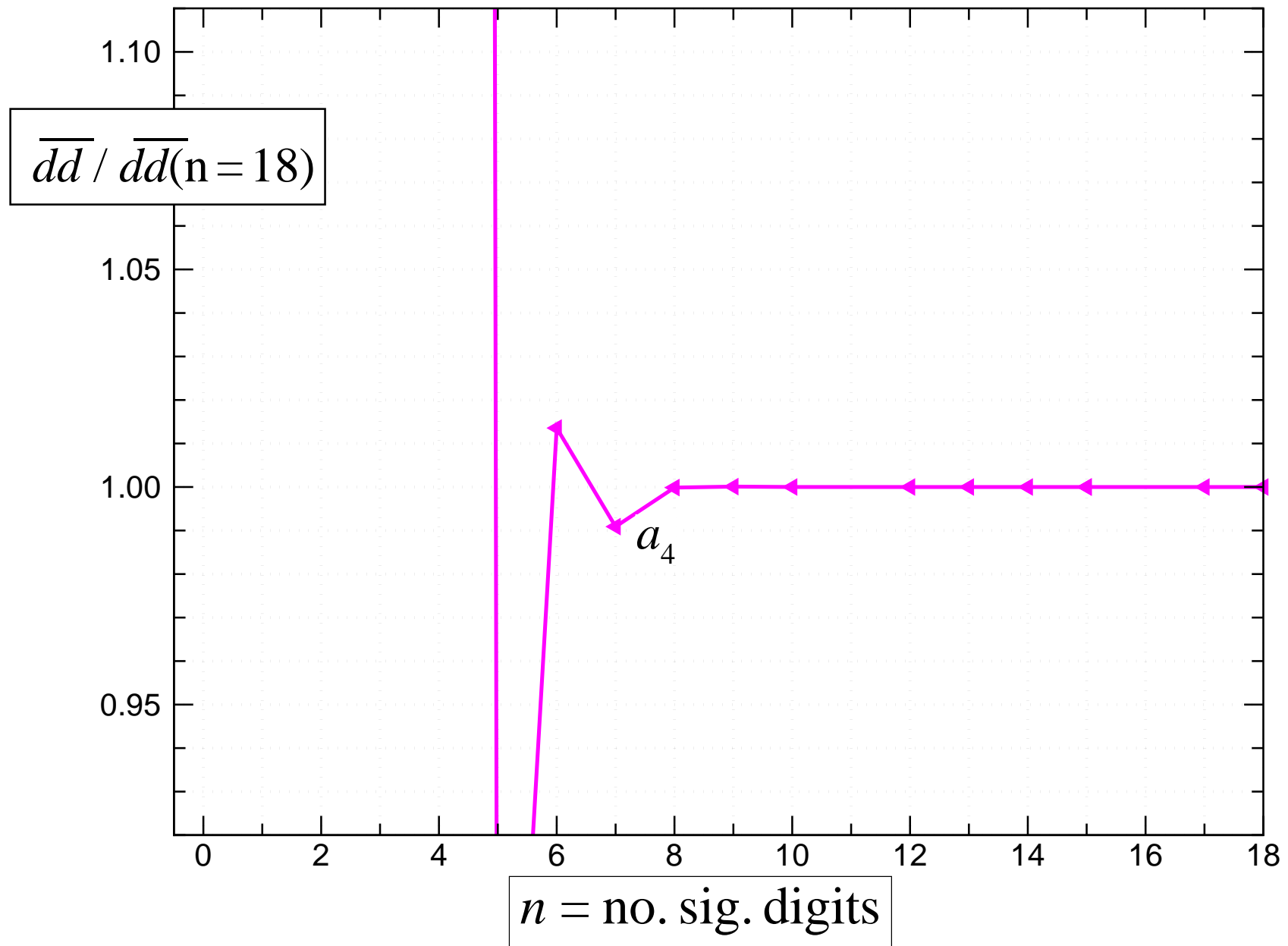
What happens to  $\overline{dd}$  if we round parameter  $a_2$  at its  $n^{\text{th}}$  significant digit?



What happens to  $\overline{dd}$  if we round parameter  $a_3$  at its  $n^{\text{th}}$  significant digit?

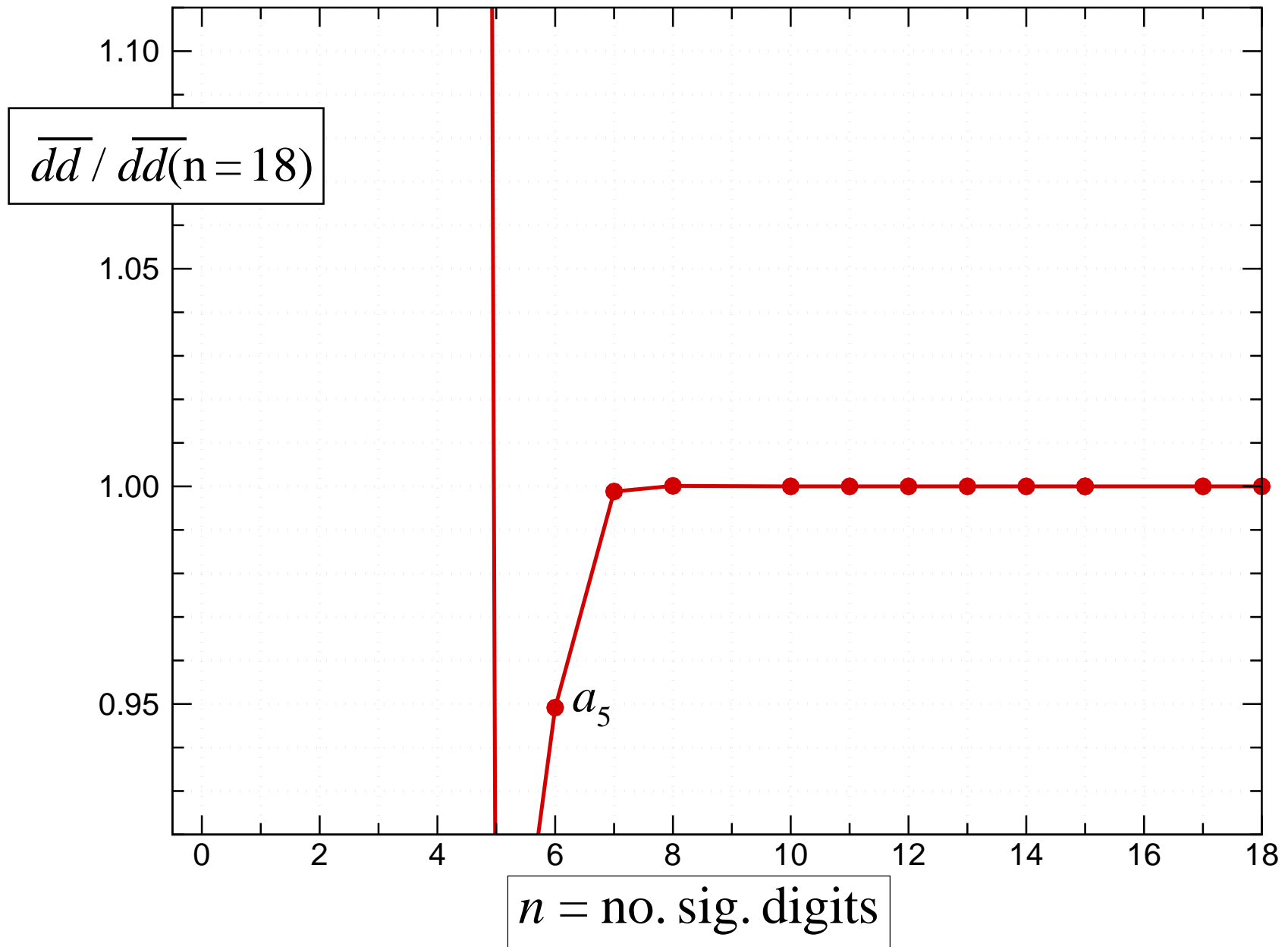


What happens to  $\overline{dd}$  if we round parameter  $a_4$  at its  $n^{\text{th}}$  significant digit?

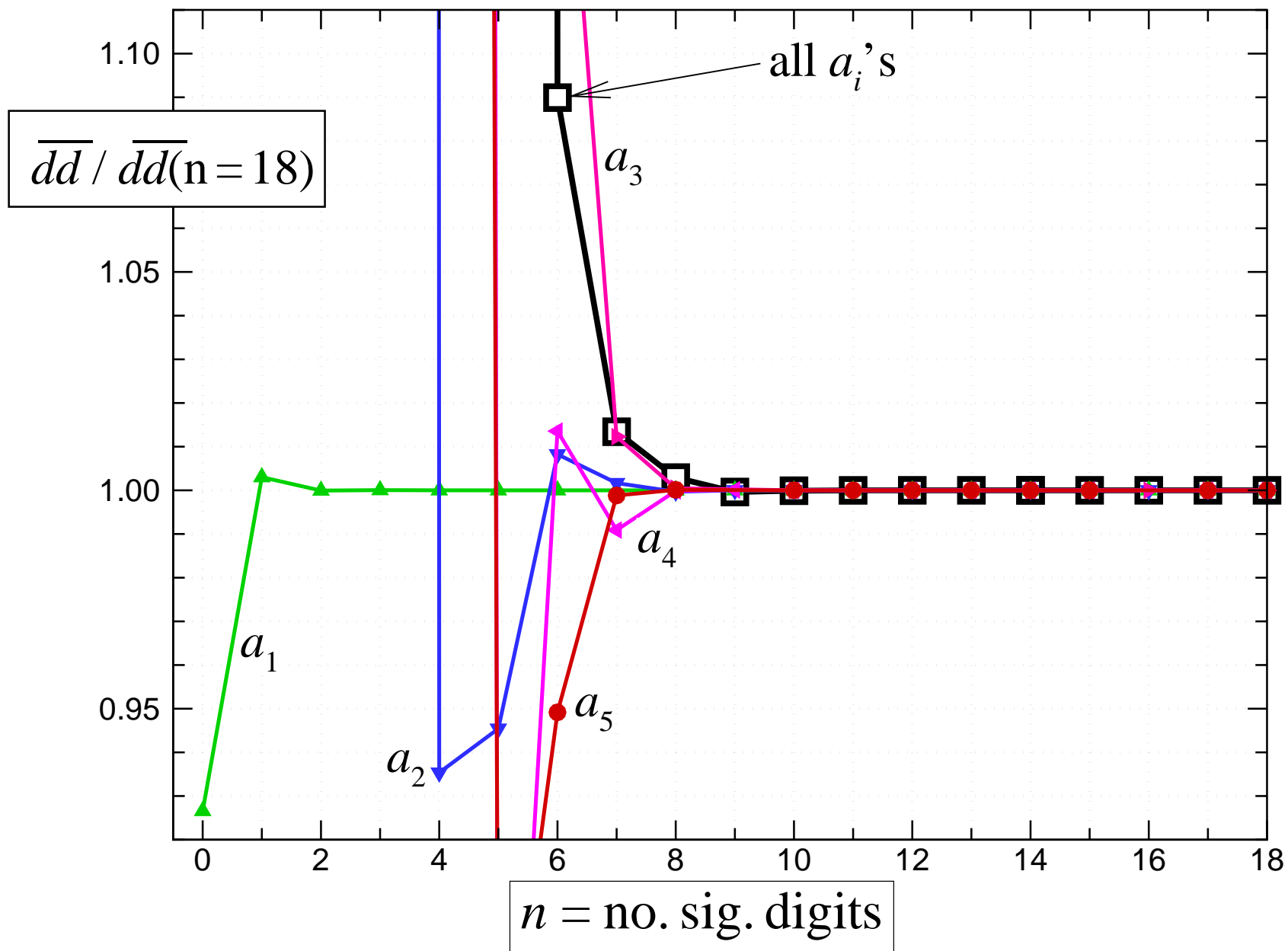




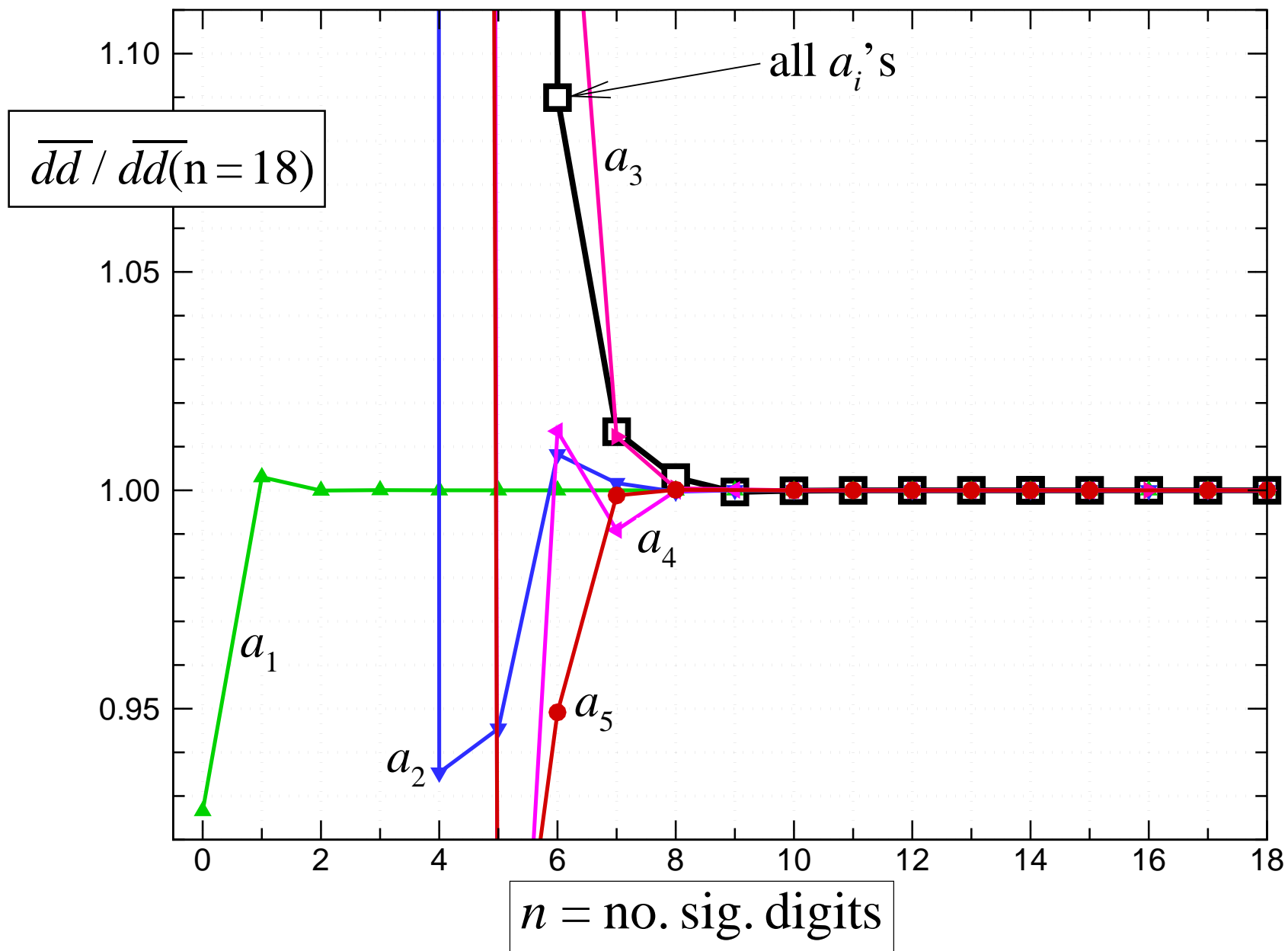
What happens to  $\overline{dd}$  if we round parameter  $a_5$  at its  $n^{\text{th}}$  significant digit?



And what happens if we round **all**  $a_i$  parameters at their  $n^{\text{th}}$  significant digit?



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*This is silly! There must be a better way of rounding!*

# Do the statistical uncertainties in the fitted parameters provide any guidance ?

**Table II.** Parameters of “X-representation” potential energy function from fit to  $\text{Mg}_2(X^1\Sigma_g^+)$  data

$$V(r) = \sum_{i=1}^n a_i \xi(r)^i \quad \text{with} \quad \xi(r) = \frac{r - R_m}{r + b R_m}$$

parameter	uncertainty
$R_m$	$\pm 0.000040$
$a_1$	$\pm 0.0$
$a_2$	$\pm 0.00038 \times 10^4$
$a_3$	$\pm 0.0040 \times 10^4$
$a_4$	$\pm 0.045 \times 10^5$
$a_5$	$\pm 0.046 \times 10^5$
$a_6$	$\pm 0.11 \times 10^5$
$a_7$	$\pm 0.12 \times 10^6$
$a_8$	$\pm 0.66 \star \times 10^6$
$a_9$	$\pm 0.5(160) \star \times 10^6$
$a_{10}$	$\pm 1.8 \star \times 10^6$
$a_{11}$	$\pm 0.83 \star \times 10^6$
$\overline{dd}$	$1.46224$ <i>is the dimensionless RMS Deviation</i>

$\star$  the 95% confidence limit uncertainty in this parameter is greater than 100% of its value.

Some years ago we examined the effect of rounding off fitted parameters at the  $n^{\text{th}}$  digit of the uncertainty in each parameter.<sup>1</sup>

For three fitting functions applied to two different data sets we found ...

model	Dunham fit to HF	Potential fit to HF	Dunham fit to I <sub>2</sub>	NDE fit to I <sub>2</sub>
# data	326	326	9552	9552
# param.	28	14	47	26
$\overline{dd}(n = 1)$	10.20	7959.	$> 10^5$	$> 10^5$
$\overline{dd}(n = 2)$	2.541	835.4	$> 10^5$	97135.
$\overline{dd}(n = 3)$	0.996	78.82	17966.	$> 10^5$
$\overline{dd}(n = 4)$	0.904	14.99	2668.	41868.
$\overline{dd}(n = 6)$	0.903	1.058	3.111	351.9
$\overline{dd}(n = 8)$	0.903	1.051	1.369	4.067
$\overline{dd}(n = 10)$	0.903	1.051	1.347	1.422
$\overline{dd}(n = 12)$	0.903	1.051	1.329	1.383

<sup>1</sup>R.J. Le Roy, *J. Mol. Spectrosc.* **191**, 223 (1998).

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Clearly, *no useful criterion here!*

This led us to develop the *Sequential Rounding and Refitting procedure*

<sup>2</sup>R.J. Le Roy, *J. Mol. Spectrosc.* **191**, 223 (1998).

The *Sequential Rounding and Refitting (SRR) procedure*

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- With that second parameter *also fixed* at its rounded value, repeat the fit to optimize the remaining parameters
- iterate this procedure until the last parameter is rounded.
- The final  $\overline{dd}$  and final total # sig. digits are *insensitive* to the order in which the parameters are rounded!

Our experience indicates that, the cumulative effect of applying the the **SRR** procedure with each stage of **R**ounding being performed at the **first** digit of the parameter uncertainty, usually only increases  $\overline{dd}$  in its  $3^{rd}$  or  $4^{th}$  significant digit.

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***Now apply it to our Mg<sub>2</sub> data analysis !***

**Table IV.** Parameters of “X-representation” potential energy function from fit to  $\text{Mg}_2(X^1\Sigma_g^+)$

$$V(r) = \sum_{i=1}^n a_i \xi(r)^i \quad \text{with} \quad \xi(r) = \frac{r - R_m}{r + b R_m}$$

parameter	uncertainty	after <i>S.R.R.</i>
$R_m$	$\pm 0.000040$	3.890423(40)
$a_1$	$\pm 0.0$	[0.0]
$a_2$	$\pm 0.00038 \times 10^4$	7.053263(3800) $\times 10^3$
$a_3$	$\pm 0.0040 \times 10^4$	$-1.78875(400) \times 10^4$
$a_4$	$\pm 0.045 \times 10^5$	2.2467(450) $\times 10^4$
$a_5$	$\pm 0.046 \times 10^5$	$-1.501(460) \times 10^4$
$a_6$	$\pm 0.11 \times 10^5$	$-5.196(1100) \times 10^4$
$a_7$	$\pm 0.12 \times 10^6$	1.696(1200) $\times 10^5$
$a_8$	$\pm 0.66 \star \times 10^6$	$-3.07(66) \star \times 10^5$
$a_9$	$\pm 0.5(160) \star \times 10^6$	7.5(160) $\star \times 10^6$
$a_{10}$	$\pm 1.8 \star \times 10^6$	$-1.2(18) \star \times 10^6$
$a_{11}$	$\pm 0.83 \star \times 10^6$	7.(83) $\star \times 10^5$
$\overline{dd}$	1.46224	1.11932
#digits	198	38

$\star$  the 95% confidence limit uncertainty in this parameter is greater than 100% of its value.

**Table I** Parameters of “X-representation” potential energy function from fit to  $\text{Mg}_2(X^1\Sigma_g^+)$  data

$$V(r) = \sum_{i=1}^n a_i \xi(r)^i \quad \text{with} \quad \xi(r) = \frac{r - R_m}{r + b R_m}$$

parameter		<i>after S.R.R.</i>	
$R_m$	[3.89039]	3.890423(40)	3.890398(40)
$a_1$	$-0.770548964164001222 \times 10^{-2}$	[0.0]	0.0
$a_2$	$0.705289125191954554 \times 10^4$	7.053263(3800) $\times 10^3$	7.056201(2100) $\times 10^3$
$a_3$	$-0.179327568767261764 \times 10^5$	-1.78875(400) $\times 10^4$	-1.79298(290) $\times 10^4$
$a_4$	$0.228278059421389626 \times 10^5$	2.2467(450) $\times 10^4$	2.2331(310) $\times 10^4$
$a_5$	$-0.144881409083685430 \times 10^5$	-1.501(460) $\times 10^4$	-1.108(140) $\times 10^4$
$a_6$	$-0.638841357804591826 \times 10^5$	-5.196(1100) $\times 10^4$	-6.446(910) $\times 10^4$
$a_7$	$0.201722011755478365 \times 10^6$	1.696(1200) $\times 10^5$	1.133(580) $\times 10^5$
$a_8$	$-0.286947115902508434 \times 10^6$	-3.07(66)★ $\times 10^5$	1.6(16)★ $\times 10^5$
$a_9$	$0.528096212291666190 \times 10^6$	7.5(160)★ $\times 10^6$	-4.9(21) $\times 10^5$
$a_{10}$	$-0.841629359994647559 \times 10^6$	-1.2(18)★ $\times 10^6$	3.(1) $\times 10^5$
$a_{11}$	$0.510277917592615297 \times 10^6$	7.(83)★ $\times 10^5$	
$\overline{dd}$	1.46224	1.11932	1.11968(+0.03%)
#digits	180	38	36

★ the 95% confidence limit uncertainty in this parameter is greater than 100% of its value.

**Table V.** Parameters of “X-representation” potential energy function from fit to  $\text{Mg}_2(X^1\Sigma_g^+)$  data

$$V(r) = \sum_{i=1}^n a_i \xi(r)^i \quad \text{with} \quad \xi(r) = \frac{r - R_m}{r + b R_m}$$

parameter		<i>after S.R.R.</i>	
$R_m$	[3.89039]	3.890398(40)	3.890356(35)
$a_1$	$-0.770548964164001222 \times 10^{-2}$	0.0	0.0
$a_2$	$0.705289125191954554 \times 10^4$	7.056201(2100) $\times 10^3$	7.051573(160) $\times 10^3$
$a_3$	$-0.179327568767261764 \times 10^5$	-1.79298(290) $\times 10^4$	-1.79357(280) $\times 10^4$
$a_4$	$0.228278059421389626 \times 10^5$	2.2331(310) $\times 10^4$	2.3059(120) $\times 10^4$
$a_5$	$-0.144881409083685430 \times 10^5$	-1.108(140) $\times 10^4$	-1.481(90) $\times 10^4$
$a_6$	$-0.638841357804591826 \times 10^5$	-6.446(910) $\times 10^4$	-7.429(700) $\times 10^4$
$a_7$	$0.201722011755478365 \times 10^6$	1.133(580) $\times 10^5$	2.453(240) $\times 10^5$
$a_8$	$-0.286947115902508434 \times 10^6$	1.6(16)★ $\times 10^5$	-2.61(31) $\times 10^5$
$a_9$	$0.528096212291666190 \times 10^6$	-4.9(21) $\times 10^5$	9.(2) $\times 10^4$
$a_{10}$	$-0.841629359994647559 \times 10^6$	3.(1) $\times 10^5$	
$a_{11}$	$0.510277917592615297 \times 10^6$		
	$10^5$		
$\overline{dd}$	1.46224	1.11968(+0.03%)	1.12387(+0.38%)
#digits	198	36	35

★ the 95% confidence limit uncertainty in this parameter is greater than 100% of its value.



Use of a different analytic model can lead to fits requiring fewer parameters/digits.

For example, rather than using a simple “X-representation” polynomial expansion to represent the potential:

$$V(r) = \sum_{i=1}^n a_i \xi(r)^i \quad \text{with} \quad \xi(r) = \frac{r - R_m}{r + b R_m}$$

★ Use a “Morse/Lennard-Jones” (MLR) function that has explicit parameters to define the well depth and equilibrium distance, and an algebraic form that incorporates the correct theoretical inverse-power-sum long-range tail.

If we define  $u_{\text{LR}}(r) = \frac{C_{m_1}}{r^{m_1}} + \frac{C_{m_2}}{r^{m_2}} + \dots$  we can write

$$V_{\text{MLR}}(r) = \mathcal{D}_e \left\{ 1 - \frac{u_{\text{LR}}(r)}{u_{\text{LR}}(r_e)} e^{-\beta(r) y_p^{\text{eq}}(r)} \right\}^2$$

$$\xrightarrow{r \gg r_e} \mathcal{D}_e - \left[ \frac{2\mathcal{D}_e e^{-\beta_\infty}}{u_{\text{LR}}(r_e)} \right] u_{\text{LR}}(r) = \mathcal{D}_e - \frac{C_{m_1}}{r^{m_1}} - \frac{C_{m_2}}{r^{m_2}} - \dots$$

in which  $\beta(r) = \beta_\infty y_p^{\text{ref}}(r) + [1 - y_p^{\text{ref}}(r)] \sum_{i=0}^{N_\beta} \beta_i y_q^{\text{ref}}(r)^i$

and  $\beta_\infty = \ln\{2\mathcal{D}_e/u_{\text{LR}}(r_e)\}$ , where  $y_q^{\text{ref}}(r) \equiv \frac{r^q - r_{\text{ref}}^q}{r^q + r_{\text{ref}}^q}$

Fitted MLR potentials require fewer expansion parameters to attain a good fit.

**Table VI.** Parameters for the “X-representation” (column 1) and MLR (others) potentials for  $\text{Mg}_2(X^1\Sigma_g^+)$  reported by Knöckel *et al.* (2013) (columns 1 and 2), and those determined here following application of our **SRR** procedure (columns 2... ).

	“X – representation” potentials		Morse/Long – Range (MLR) potentials		
	Knöckel <i>et al.</i> (2013)	Knöckel <i>et al.</i> (2013)	Knöckel <i>et al.</i> (2013)	<i>present work</i>	
$\mathcal{D}_e$	[430.472]	430.369	430.393(5)	430.394(5)	
$r_e$	[3.89039]	3.89039	3.890359(62)	3.890416(34)	
$a_0 / \beta_0$	[0.0]	– 166551033592512887	–1.66525(43)	–1.58978(10)	
$a_1 / \beta_1$	$-0.770548964164001222 \times 10^{-2}$	–00294159018281270335	–0.0314(42)	–2.105(1)	
$a_2 / \beta_2$	$0.705289125191954554 \times 10^4$	–104633090905496307	–1.0413(290)	–7.983(7)	
$a_3 / \beta_3$	$-0.179327568767261764 \times 10^5$	–0324453179411172965	–0.24(11)	–1.20(3)	
$a_4 / \beta_4$	$0.228278059421389626 \times 10^5$	–184420236755870848	–2.35(70)	–4.5(1)	
$a_5 / \beta_5$	$-0.144881409083685430 \times 10^5$	114228141585836918	1.0(11)★	5.3(3)	
$a_6 / \beta_6$	$-0.638841357804591826 \times 10^5$	119434493806085307	6.0(48)	–0.2(3)★	
$a_0 / \beta_7$	$0.201722011755478365 \times 10^6$	–773024102172378935	–16.45(110)	0.6(7)★	
$a_8 / \beta_8$	$-0.286947115902508434 \times 10^6$	753234036484323610	12.0(68)		
$a_9 /$	$0.528096212291666190 \times 10^6$				
$a_{10} /$	$-0.841629359994647559 \times 10^6$				
$a_{11}, /$	$0.510277917592615297 \times 10^6$				
$\overline{dd}$	1.46224	1.21346	1.11822	1.11930(+0.01%) 1.1	
<i>#digits</i>	180	174	43	37	

**Table VII.** Parameters for the “X-representation” (column 1) and MLR (others) potentials for  $\text{Mg}_2(X^1\Sigma_g^+)$  reported by Knöckel *et al.* (2013) (columns 1 and 2), and those determined here following application of our **SRR** procedure (columns ... ).

	“X – representation” potentials		Morse/Long – Range (MLR) potentials		
	Knöckel <i>et al.</i> (2013)		<i>present work</i>		
$\mathcal{D}_e$	[430.472]	430.393(5)	430.394(5)	430.396(4)	430.396(4)
$r_e$	[3.89039]	3.890359(62)	3.890416(34)	3.89042(34)	3.89042(31)
$a_0 / \beta_0$	[0.0]	−166525(43)	−1.58978(10)	−1.58977(10)	−1.58977(9)
$a_1 / \beta_1$	$−0.770548964164001222 \times 10^{-2}$	−00314(42)	−2.105(1)	−0.2104(7)	−0.2104(6)
$a_2 / \beta_2$	$0.705289125191954554 \times 10^4$	−10413(290)	−7.983(7)	−0.794(5)	−0.794(3)
$a_3 / \beta_3$	$−0.179327568767261764 \times 10^5$	−024(11)	−1.20(3)	−0.14(1)	−0.14(1)
$a_4 / \beta_4$	$0.228278059421389626 \times 10^5$	−235(70)	−4.5(1)	−0.51(1)	−0.51(1)
$a_5 / \beta_5$	$−0.144881409083685430 \times 10^5$	10(11)★	5.3(3)	0.75(6)	0.75(5)
$a_6 / \beta_6$	$−0.638841357804591826 \times 10^5$	60(48)	−0.2(3)★	0.0(2)★	
$a_0 / \beta_7$	$0.201722011755478365 \times 10^6$	−1645(110)	0.6(7)★		
$a_8 / \beta_8$	$−0.286947115902508434 \times 10^6$	120(68)			
$a_9 /$	$0.528096212291666190 \times 10^6$				
$a_{10} /$	$−0.841629359994647559 \times 10^6$				
$a_{11}, /$	$0.510277917592615297 \times 10^6$				
$\overline{dd}$	1.46224	1.11822	1.11930(+0.01%)	1.11973(+0.04%)	1.11973(+0.04%)
<i>#digits</i>	180	43	37	33	32

**Table VIII.** Parameters for the “X-representation” (column 1) and MLR (others) potentials for  $\text{Mg}_2(X^1\Sigma_g^+)$  reported by Knöckel *et al.* (2013) (columns 1 and 2), and those determined here following application of our **SRR** procedure (columns ... ).

	“X – representation” potentials		Morse/Long – Range (MLR) potentials		
	Knöckel <i>et al.</i> (2013)		<i>present work</i>		
$\mathcal{D}_e$	[430.472]	430.394(5)	430.396(4)	430.396(4)	430.385(4)
$r_e$	[3.89039]	3.890416(34)	3.89042(34)	3.89042(31)	3.890418(31)
$a_0 / \beta_0$	[0.0]	−158978(10)	−1.58977(10)	−1.58977(9)	−1.71326(9)
$a_1 / \beta_1$	$−0.770548964164001222 \times 10^{-2}$	−2105(1)	−0.2104(7)	−0.2104(6)	0.0652(6)
$a_2 / \beta_2$	$0.705289125191954554 \times 10^4$	−7983(7)	−0.794(5)	−0.794(3)	−1.109(6)
$a_3 / \beta_3$	$−0.179327568767261764 \times 10^5$	−120(3)	−0.14(1)	−0.14(1)	−0.15(3)
$a_4 / \beta_4$	$0.228278059421389626 \times 10^5$	−45(1)	−0.51(1)	−0.51(1)	−2.279(2)
$a_5 / \beta_5$	$−0.144881409083685430 \times 10^5$	53(3)	0.75(6)	0.75(5)	
$a_6 / \beta_6$	$−0.638841357804591826 \times 10^5$	−02(3)★	0.0(2)★		
$a_0 / \beta_7$	$0.201722011755478365 \times 10^6$	06(7)★			
$a_8 / \beta_8$	$−0.286947115902508434 \times 10^6$				
$a_9 /$	$0.528096212291666190 \times 10^6$				
$a_{10} /$	$−0.841629359994647559 \times 10^6$				
$a_{11}, /$	$0.510277917592615297 \times 10^6$				
$\overline{dd}$	1.46224	1.11930(+0.01%)	1.11973(+0.04%)	1.11973(+0.00%)	1.12975(−0.01%)
<i>#digits</i>	180	37	33	32	33

**Table IX.** Parameters for the “X-representation” (column 1) and MLR (others) potentials for  $\text{Mg}_2(X^1\Sigma_g^+)$  reported by Knöckel *et al.* (2013) (columns 1 and 2), and those determined here following application of our ***SRR*** procedure (columns ... ).

	“X – representation” potentials	Morse/Long – Range (MLR) potentials		
	Knöckel <i>et al.</i> (2013)	<i>present work</i>		
$\mathcal{D}_e$	[430.472]	430.396(4)	430.396(4)	430.385(4)
$r_e$	[3.89039]	3.89042(34)	3.89042(31)	3.890418(35)
$a_0 / \beta_0$	[0.0]	−158977(10)	−1.58977(9)	−1.71326(20)
$a_1 / \beta_1$	$−0.770548964164001222 \times 10^{-2}$	−02104(7)	−0.2104(6)	0.0652(12)
$a_2 / \beta_2$	$0.705289125191954554 \times 10^4$	−0794(5)	−0.794(3)	−1.109(6)
$a_3 / \beta_3$	$−0.179327568767261764 \times 10^5$	−014(1)	−0.14(1)	−0.15(3)
$a_4 / \beta_4$	$0.228278059421389626 \times 10^5$	−051(1)	−0.51(1)	−2.279(26)
$a_5 / \beta_5$	$−0.144881409083685430 \times 10^5$	075(6)	0.75(5)	
$a_6 / \beta_6$	$−0.638841357804591826 \times 10^5$	00(2)★		
$a_0 / \beta_7$	$0.201722011755478365 \times 10^6$			
$a_8 / \beta_8$	$−0.286947115902508434 \times 10^6$			
$a_9 /$	$0.528096212291666190 \times 10^6$			
$a_{10} /$	$−0.841629359994647559 \times 10^6$			
$a_{11}, /$	$0.510277917592615297 \times 10^6$			
$\overline{dd}$	1.46224	1.11973(+0.04%)	1.11973(+0.00%)	1.12975(+0.61%)
<i>#digits</i>	180	33	32	32

**Table IX.** Parameters for the “X-representation” (column 1) and MLR (others) potentials for  $\text{Mg}_2(X^1\Sigma_g^+)$  reported by Knöckel *et al.* (2013) (columns 1 and 2), and those determined here following application of our ***SRR*** procedure (columns ... ).

	“X – representation” potentials		Morse/Long – Range (MLR) potentials	
	Knöckel <i>et al.</i> (2013)		<i>present work</i>	
$\mathcal{D}_e$	[430.472]	430.396(4)	<b>430.396(4)</b>	430.385(4)
$r_e$	[3.89039]	3.89042(34)	<b>3.89042(31)</b>	3.890418(35)
$a_0 / \beta_0$	[0.0]	−158977(10)	<b>−1.58977(9)</b>	−1.71326(20)
$a_1 / \beta_1$	$−0.770548964164001222 \times 10^{-2}$	−02104(7)	<b>−0.2104(6)</b>	0.0652(12)
$a_2 / \beta_2$	$0.705289125191954554 \times 10^4$	−0794(5)	<b>−0.794(3)</b>	−1.109(6)
$a_3 / \beta_3$	$−0.179327568767261764 \times 10^5$	−014(1)	<b>−0.14(1)</b>	−0.15(3)
$a_4 / \beta_4$	$0.228278059421389626 \times 10^5$	−051(1)	<b>−0.51(1)</b>	−2.279(26)
$a_5 / \beta_5$	$−0.144881409083685430 \times 10^5$	075(6)	<b>0.75(5)</b>	
$a_6 / \beta_6$	$−0.638841357804591826 \times 10^5$	00(2)★		
$a_0 / \beta_7$	$0.201722011755478365 \times 10^6$			
$a_8 / \beta_8$	$−0.286947115902508434 \times 10^6$			
$a_9 /$	$0.528096212291666190 \times 10^6$			
$a_{10} /$	$−0.841629359994647559 \times 10^6$			
$a_{11}, /$	$0.510277917592615297 \times 10^6$			
$\overline{dd}$	1.46224	1.11973(+0.04%)	<b>1.11973(+0.00%)</b>	1.12975(+0.61%)
<i>#digits</i>	180	33	<b>32</b>	32

# Conclusions

- without some indication of uncertainties, a user cannot trust reported parameters
- parameter uncertainties alone are not a reliable guide to appropriate rounding
- reporting excessive numbers of digits greatly magnifies opportunities for transcription errors along the ‘supply chain’ from analysis to user
- *Sequential Rounding and Refitting* (**SRR**) has proven to be a robust and reliable way of optimally rounding a fitted parameter set.
  - the order in which the *Sequential Rounding* is performed appears not to matter
  - for higher precision, the rounding may be performed at the second or third digit of the parameter uncertainty
- **SRR** should be straightforward to implement with virtually *any* least-squares program
- a robust general purpose subroutine for performing linear or non-linear least-squares fits with **SRR**, named **NLLSSRR**, for *Non-Linear Least-Squares with Sequential Rounding and Refitting* may be downloaded freely from the URL <http://scienide2.uwaterloo.ca/~rleroy/fitting/>