Progress towards an evaluation of the ⁷Be system with AZURE2

James deBoer

University of Notre Dame and JINA





R-matrix details

Using the Brune basis

```
Using "(light, heavy)"  (\alpha,^3 \text{He}) \\  (p_0,^6 \text{Li}) \\  (p_1,^6 \text{Li}) \\  \text{Haven't been able to successfully fit } (p_2,6 \text{Li})
```

Step 1: Compile data sets

Ian Thompson

Pulled all ${}^{3}\text{He}+\alpha$, $\alpha+{}^{3}\text{He}$, ${}^{7}\text{Li}+p$ and $p+{}^{7}\text{Li}$ data from EXFOR

Meta data sheet

Kinematic, final state, data type, energy range, etc.

Step 2: Take a subset of data

About 50 data sets, just taking 13 representatives

Step 3: Summarize systematic uncertainties

Very important to note that several data sets obtain their absolute cross section scale by normalizing to previous measurements

Reaction	Reference	EXFOR ID	Syst. Unc. (%)	Comments
$^3{\rm He}(\alpha,\alpha)$	Barnard et al. [1]	A1269002	5 (total)	$d\sigma/d\Omega$, Data from Hale
$^3{\rm He}(\alpha,\alpha)$	Tombrello and Parker [2]	A1295002	5 (total)	$d\sigma/d\Omega$
$^6\mathrm{Li}(p,p)$	McCray [3]	A1410002	5	$d\sigma/d\Omega$
$^6\mathrm{Li}(p,p_{0,1})$	Harrison and Whitehead [4]	C1003002	N to [3]	$d\sigma/d\Omega$
$^6\mathrm{Li}(p, lpha)$	Elwyn et al. [5]	F0012002	9	$d\sigma/d\Omega$
$^6\mathrm{Li}(p,p)$	Fasoli et al. [6]	D0135002	N to [2]	$d\sigma/d\Omega$
$^6\mathrm{Li}(p, lpha)$	Cruz et al. [7]	O1590003	6	σ
$^6\mathrm{Li}(p,\alpha)$	Tumino et al. [8]	O1221002	N to [5]	σ (THM)
$^6\mathrm{Li}(p, lpha)$	Gemeinhardt et al. [9]	A1367002	5	σ
$^6\mathrm{Li}(p,\alpha)$	Bertrand et al. [10]	A1513005	unclear	$d\sigma/d\Omega$
$^6\mathrm{Li}(p,\alpha)$	Shinozuka et al. [11]	F0005004	14	$d\sigma/d\Omega$
$^6\mathrm{Li}(p,p)$	Skill et al. [12]	A0541002	_	$d\sigma/d\Omega$
$^6\mathrm{Li}(p,p)$	Soukeras et al. [13]	O2277002		$d\sigma/d\Omega$
$^3{\rm He}(\alpha,\alpha/p_{0,1})$	Spiger and Tombrello [14]	A1094007	1.5	$d\sigma/d\Omega$, Thompson revised

Step 4: Look for outliers

Spiger and Tombrello

Very small systematic uncertainty estimate of 1.5%, unrealistic.

Inconsistent data

Jeronymo *et al.*, (p,α) angular distributions Mohr *et al.*, (p,p) angular distributions etc.

Step 5: Fit as excitation functions or angular distributions

Still working this out, some preliminary decisions made

Step 6: Obtain a good R-matrix fit

Not fully achieved

Looks pretty up to about 8 or 9 MeV excitation energy

Having a hard time above the p1 threshold

Fitting some p1 data, not yet fitting p2 data

Comp	ound	Nucleus Levels	
ıclude	Fix?	Level Spin	Energy [MeV]
V	V	3/2-	0
v	✓	1/2-	0.429
v		7/2-	4.5636
v		5/2-	6.6545
v		5/2-	7.1573
v		1/2-	7.7667
V		5/2-	9.4709
V		7/2-	9.6768
V	~	1/2-	17
V	~	1/2-	20
V	✓	1/2+	20
V	✓	3/2-	20
V	✓	3/2+	20
V	✓	5/2-	20
V	✓	5/2+	20
V	✓	7/2-	20
V	✓	7/2+	20
V	✓	9/2-	20
V	✓	9/2+	20

Step 7: Perform MCMC uncertainty estimation calculations [50 priors = [51 stats.uniform(0,10), #1/2- FES alph 52 stats.uniform(0,10), #1/2- FES prot 53 stats.uniform(7,7, 0,3) #1/2- purp 54 stats.uniform(7,7, 0,3) #1/2- purp 55 stats.uniform(7,7, 0,3) #1/2- purp 56 priors = [57 stats.uniform(7,7, 0,3) #1/2- purp 57 stats.uniform(7,7, 0,3) #1/2- purp 58 priors = [59 priors = [50 priors = [50 priors = [51 stats.uniform(0,10), #1/2- FES prior 57 stats.uniform(7,7, 0,3) #1/2- purp 58 priors = [59 priors = [50 priors = [50 priors = [51 stats.uniform(0,10), #1/2- FES prior 58 priors = [59 priors = [50 priors = [50 priors = [51 stats.uniform(0,10), #1/2- FES prior 59 priors = [50 priors = [50 priors = [51 stats.uniform(0,10), #1/2- FES prior 59 priors = [50 priors = [50 priors = [51 stats.uniform(0,10), #1/2- FES prior 50 priors = [51 priors =

Using the Bayesian R-matrix Inference Code Kit (BRICK) developed by Daniel Odell at Ohio University (post doc of Daniel Phillips and collaborator of Carl Brune)

Give each fit parameter a prior

Usually it is uniform (no prior uncertainty information)

Systematic uncertainties may be given a Gaussian or Lognormal distribution if they have an independent determination of the absolute cross section

```
stats.uniform(0,10), #1/2- FES alpha ANC
      stats.uniform(0,10), #1/2- FES proton ANC 1
      stats.uniform(7.7, 0.3), #1/2- unbound energy 1
      stats.uniform(0,10000), #1/2- unbound alpha width
      stats.uniform(-2e6,2e6), #1/2- unbound proton width 1
      stats.uniform(0,1e6), #1/2- unbound proton width 2
      stats.uniform(0,1e8), #1/2- BGP alpha width
      stats.uniform(0,1e9), #1/2- BGP proton width 1
      stats.uniform(-1e7, 1e7), #1/2- BGP proton width 2
      stats.uniform(0,1e9), #1/2+ BGP alpha width
      stats.uniform(0,1e9), #1/2+ BGP proton width 1
      stats.uniform(0,1e9), #1/2+ BGP proton 1 width
      stats.uniform(-10,10), #3/2- GS alpha ANC
      stats uniform(0 10) #3/2- GS proton ANC 1
        stats.norm(1, 0.05), # Barnard
        stats.norm(1, 0.05), # Tombrello and Parker
        stats.norm(1, 0.05), #McCray
        stats.uniform(0, 10), #Harrison and Whitehead
        stats.norm(1, 0.09), #Elwyn
        stats.uniform(0, 10), #McCray start
        stats.uniform(0, 10),
        stats.uniform(0, 10),
113
        stats.uniform(0, 10),
114
        stats.uniform(0, 10),
        stats.uniform(0, 10), #McCray stop
        stats.uniform(0, 10), #Fasoli start
        stats.uniform(0, 10),
        stats.uniform(0, 10),
119
        stats.uniform(0, 10),
        stats.uniform(0, 10),
121
        stats.uniform(0, 10),
        stats.uniform(0, 10), #Fasoli stop
```

So that's where I'm at

Biggest problems

Having trouble pinning down the level structure above 9 MeV excitation energy

LOTS of data, which is good, but takes a lot of work to input into the calculations (data + meta data)

The bright side

LOTS of data

A large fraction are pretty consistent! (outlier data more easily identifiable)