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Identification of Robot Dynamics from Motor Currents/Torques with Unknown Signs

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***Abstract*—Robot dynamic identification techniques rely on the quality and completeness of the signals available as inputs, typically joint positions and motor currents or joint torques. These signals are often noisy and filtering operations are required before using them for identification. Moreover, some robot control units (e.g., in the KUKA KR5 Sixx) return the user only the absolute values of the motor currents (or of the torques), thus preventing a correct dynamic estimation. We present a method for the identification of the robot dynamic model when the motor torques/currents have unknown signs. The method consists in solving a sequence of constrained optimization problems, exploiting physical feasibility constraints. A tree of solutions is built, and the branches leading to unfeasible solutions are pruned. As output, the torque signs are estimated together with the resulting robot dynamic model.**

***Index Terms*—Identification, Dynamics, Optimization**

I. Introduction

An accurate dynamic model is of paramount importance for the design of robot control laws with superior performance [1]. To set up a reliable estimation of the dynamic model, regression techniques are widely employed [2], [3], using the linear dependence of the robot equations on a set of *dynamic coefficients* $\boldsymbol{\pi}_R \in \mathbb{R}^\rho$ [4], also known as *base parameters* [5]. These are (possibly nonlinear) combinations of the standard *dynamic parameters* of the robot, i.e., the mass, the position of the center of mass (CoM), and the elements of the symmetric inertia tensor of each of its links. For a n-dof robot, one has $\boldsymbol{p} \in \mathbb{R}^{10n}$ dynamic parameters. In general, the dynamic parameters are not individually identifiable: some do not appear in the model, while most of them affect the dynamics only in combinations. Only these combinations (i.e., the dynamic coefficients) are identifiable quantities.

Identification of the robot dynamic coefficients is sufficient for motion control, when using the dynamic model in the Euler-Lagrange form. In other situations, it is necessary to know the values of the robot dynamic parameters: for instance, when performing dynamic simulations via a CAD-based robot software (like CoppeliaSim [6]) or when using the recursive numerical Newton-Euler algorithm to implement torque-level control laws (such as feedback linearization) under hard real-time constraints.

There are several approaches that address the problem of retrieving a *feasible* set of dynamic parameters from the identified dynamic coefficients, employing semi-definite programming techniques with Linear Matrix Inequalities [7]–[9] or nonlinear optimization methods (e.g., using Simulated Annealing, as in [10]). Feasible parameters are those that preserve some physical consistency properties, such as positive link masses, positive definite link inertia tensors that satisfy the triangular inequality, and link CoMs inside a geometric convex hull. In [10], we proposed a flexible optimization framework to retrieve a set of feasible dynamic parameters that is capable to deal also with nonlinear or conditional constraints and with user-defined bounds, which are treated as penalties in the objective function (henceforth, Penalty-Based Parameters Retrieval or PBPR algorithm).

These approaches require reliable measures from robot encoders and motor current/torque sensors, collected during the execution of sufficiently exciting trajectories. There are, however, some special cases in which only a partial information is made available by the closed architecture of the robot controller. For instance, the KUKA KR5 Sixx robot, a 6R small-size industrial manipulator, as well as the equivalent DENSO robot return only the absolute values of the motor currents. This might be an intentional choice by the manufacturer (e.g., to provide a simple monitoring signal for emergency), or may be due to the output being taken from the PWM devices driving the motors (typically, positive-encoded signals only).

In this paper, we propose a method to identify the dynamic coefficients and retrieve a feasible set of dynamic parameters for robots whose motor current/torque sensors do not return the sign of the measured quantity. This approach takes advantage of the PBPR algorithm, generating a tree of solutions with a number of possible motor information, which is progressively pruned during the identification phase, discarding the physically unfeasible sets of parameters.

The paper is organized as follows, Section II recalls the general procedure for identifying the dynamic coefficients and retrieving a set of feasible dynamic parameters. The additional steps needed to deal with the problem of missing current/torque signs are described in Sec. III. Validation results on a simulated KUKA KR5 Sixx are reported in Sec. IV and conclusions are drawn in Sec. V.

II. Preliminaries

For each link ℓ_i, $i = 1, \ldots, n$ composing a n-dof rigid robot, let m_i be the mass and let

$$ {}^i\boldsymbol{r}_{i,ci} = \begin{pmatrix} c_{ix} \\ c_{iy} \\ c_{iz} \end{pmatrix}, \quad {}^i\boldsymbol{J}_{\ell_i} = \begin{pmatrix} J_{ixx} & J_{ixy} & J_{ixz} \\ J_{ixy} & J_{iyy} & J_{iyz} \\ J_{ixz} & J_{iyz} & J_{izz} \end{pmatrix}, \quad (1) $$

be the position of the CoM and the symmetric inertia tensor with respect to the i-th link frame, respectively. Collecting the dynamic parameters of all links in three vectors $\boldsymbol{p}_1$ (with the masses m_i), $\boldsymbol{p}_2$ (with the first order moments of inertia

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$m_i\,{}^i\boldsymbol{r}_{i,ci}$) and $\boldsymbol{p}_3$ (with the second order moments of inertia, i.e., the elements of the inertia tensor ${}^i\boldsymbol{J}_{\ell_i}$), it is possible to express the robot dynamic model as

$$\boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}})\,\boldsymbol{\pi}(\boldsymbol{p}_1,\boldsymbol{p}_2,\boldsymbol{p}_3)=\boldsymbol{K}\boldsymbol{i}=\boldsymbol{\tau}, \tag{2}$$

where $\boldsymbol{q}$, $\dot{\boldsymbol{q}}$, $\ddot{\boldsymbol{q}} \in \mathbb{R}^n$ are the joint position, velocity and acceleration vectors, $\boldsymbol{i} \in \mathbb{R}^n$ and $\boldsymbol{\tau} \in \mathbb{R}^n$ are the motor current and torque vectors, and $\boldsymbol{K} = \mathrm{diag}(K_1 \ldots K_n) \in \mathbb{R}^{n\times n}$ is the matrix of current-to-torque gains. The $n \times p$ regressor matrix $\boldsymbol{Y}$, depending on time-varying functions, multiplies the vector $\boldsymbol{\pi}(\boldsymbol{p}_1,\boldsymbol{p}_2,\boldsymbol{p}_3) \in \mathbb{R}^p$ of dynamic coefficients, which appear linearly in the dynamic model (2).

The classical dynamic identification procedure is performed by collecting, at times $t = t_k$, a number $m \gg np$ of joint torque samples[1] with associated m joint position samples, while joint velocities and accelerations are obtained by off-line differentiation. For each numerical sample $(\boldsymbol{\tau}_k, \boldsymbol{q}_k, \dot{\boldsymbol{q}}_k, \ddot{\boldsymbol{q}}_k)$, with $k = 1,\ldots,m$, we have

$$\boldsymbol{Y}_k(\boldsymbol{q}_k,\dot{\boldsymbol{q}}_k,\ddot{\boldsymbol{q}}_k)\boldsymbol{\pi}=\boldsymbol{\tau}_k. \tag{3}$$

By stacking these quantities in vectors and matrices, one has

$$\overline{\boldsymbol{Y}}\boldsymbol{\pi}=\overline{\boldsymbol{\tau}}, \tag{4}$$

with $\overline{\boldsymbol{\tau}} \in \mathbb{R}^{mn}$ and $\overline{\boldsymbol{Y}} \in \mathbb{R}^{mn\times p}$. According to [5], we prune the stacked regressor $\overline{\boldsymbol{Y}}$ so as to obtain a $mn \times \rho$ matrix $\overline{\boldsymbol{Y}}_R$ with full column rank $\rho \le p$, and then identify the associated (minimal) dynamic coefficients $\boldsymbol{\pi}_R \in \mathbb{R}^\rho$ by solving an Ordinary Least-Squares (OLS) problem via pseudoinversion

$$\widehat{\boldsymbol{\pi}}_R=\overline{\boldsymbol{Y}}_R^{\#}\overline{\boldsymbol{\tau}}. \tag{5}$$

The dynamic coefficients $\widehat{\boldsymbol{\pi}}_R$ are sufficient for inverse dynamics computations on a given motion $\boldsymbol{q}(t)$ via eq. (2). In order to retrieve *feasible* values for the original dynamic parameters $\boldsymbol{p}$ providing the estimated $\widehat{\boldsymbol{\pi}}_R$, and thus achieving the same identified robot dynamics, one may use the PBPR algorithm [10]. This requires solving a nonlinear optimization problem (with bounding boxes) whose cost function is augmented by penalties activated by constraint violations:

$$\min_{\boldsymbol{p}} f(\boldsymbol{p})=\phi(\boldsymbol{p})+\gamma(\boldsymbol{p}) \qquad \text{s.t.} \quad LB \le \boldsymbol{p} \le UB. \tag{6}$$

In (6), $\gamma(\boldsymbol{p})$ provides an additive penalty for each violated problem constraint, LB and UB are the lower and the upper bounds for the parameter vector $\boldsymbol{p}$, and the objective function $\phi(\boldsymbol{p})$ can be chosen as

$$\phi_1(\boldsymbol{p})=\left\|\boldsymbol{\pi}_R(\boldsymbol{p})-\widehat{\boldsymbol{\pi}}_R\right\|^2 \quad \text{or} \quad \phi_2(\boldsymbol{p})=\left\|\overline{\boldsymbol{Y}}_R\boldsymbol{\pi}_R(\boldsymbol{p})-\overline{\boldsymbol{\tau}}\right\|^2, \tag{7}$$

where $\boldsymbol{\pi}_R(\boldsymbol{p})$ are the symbolic expressions of the (minimal) dynamic coefficients in terms of the dynamic parameters $\boldsymbol{p}$.

III. Estimating the Torque Signs and Identifying the Robot Dynamics

Assume now that each component of the stacked vector $\overline{\boldsymbol{\tau}}$ of joint torques is known only in absolute value. In vector format, this means that we know only the non-negative values $\overline{\boldsymbol{\tau}}_s = |\overline{\boldsymbol{\tau}}|$. In such situation, it is impossible to retrieve a reliable estimation of the dynamic coefficients with the available methods in the literature. In order to retrieve from $\overline{\boldsymbol{\tau}}_s$ the correct signs of the original torques, and thus properly estimate the dynamic coefficients $\boldsymbol{\pi}_R$, we take advantage of the features offered by the PBPR algorithm [10] that is capable of extracting a feasible set of dynamic parameters $\boldsymbol{p}$.

[1] We collect equivalently motor current samples, assuming that $\boldsymbol{K}$ is known.

Algorithm 1: Tree Penalty-Based Parameters retrieval (T-PBPR)

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Collect the retrieved data during an exciting trajectory: q_j(t), q̇_j(t), q̈_j(t), |τ_j(t)|, j = 1,...,n;
Extract all the s torque segments;
Build an initial regressor matrix ^{s0}Ȳ_R by evaluating Y_R
   with the smallest number s0 ≤ s of segments such that
   ^{s0}Ȳ_R is well-conditioned;
Build an initial measurements vector ^{s0}τ̄, whose elements
   are related to the rows of ^{s0}Ȳ_R;
Choose a convenient number of nodes w ≤ s0 to be
   expanded at each iteration;
for k = s0,...,s do
    if k = s0 then
        ξ ← 2^{s0};
    else
        ξ ← 2w;
    end
    Solve ξ OLS problems employing ^kȲ_R and ^kτ̄ for
       identifying the dynamic coefficients π̂_{R,i} (i = 1,...,ξ)
       (one set for each node of the tree), according to eq. (5);
    For each π̂_{R,i}, apply the PBPR algorithm in (6) using
       function φ1 in (7), and select the w nodes returning the
       lowest cost function f(p);
    Expand those w nodes only, choosing a new torque
       segment τ̄' and stacking a new block Ȳ'_R to the
       regressor matrix, yielding
       ^{k+1}Ȳ_R ← [ ^kȲ_R^T  Ȳ'_R^T ]^T and
       ^{k+1}τ̄ ← [ ^kτ̄^T  τ̄'^T ]^T;
end
Retrieve the motor torque signs that have been estimated for
   each segment by following the generated tree path;
Apply the PBPR algorithm in (6) using function φ2 in (7)
   with the complete regressor ⇒ optimal π̂_R and p̂.
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The basic hypothesis we make concerns smoothness. For each joint j, we assume that the torque $\tau_j(t)$ keeps with continuity the same sign until the signal $\tau_{j,s}$ reaches zero (up to a small threshold). Therefore, we can isolate portions of the torque signal (henceforth, *segments*) for each joint having the same (yet, unknown) sign. Each segment is related to a single joint and typically contains a different number of samples. Moreover, the segment detection procedure can be performed in any order from joint to joint.

Let $\sigma_1,\ldots,\sigma_n$ be the numbers of detected segments for joints $1,\ldots,n$, and $s = \sigma_1 + \ldots + \sigma_n$ be the total number of isolated torque segments. For each segment, the torque could be either positive or negative —a binary choice. Therefore, one should solve $S = 2^s$ identification problems, although only a small subset of the S solutions will provide feasible dynamic parameters. In principle, we may apply S runs of the PBPR algorithm, and select eventually the solution with the lowest value of the cost function in (6). This procedure is time consuming due to the exponential nature of the problem, and thus unfeasible in practice for real applications.

Therefore, we proceed more efficiently by building a tree in which each node adds a new segment to the regressor (i.e., a block of rows to the matrix $\overline{\boldsymbol{Y}}$ in (4)), branching the node for the two possible signs of the added $\overline{\boldsymbol{\tau}}$. We progressively prune the branches leading to unfeasible sets of parameters. Moreover, one expands only the 'most promising' branches to further reduce the computational effort, yielding a dramatic improvement in performance. The complete procedure, named Tree Penalty-Based Parameters Retrieval (T-PBPR), is described in Algorithm 1. The outputs of the T-PBPR algorithm are the estimated signs for each of the S (or less) torque segments and, consequently, the identified dynamic coefficients $\widehat{\boldsymbol{\pi}}_R$ together with a feasible set of dynamic parameters $\widehat{\boldsymbol{p}}$.

IV. Results

A. The KUKA KR5 robot

We have tested the T-PBPR algorithm on the KUKA KR5 Sixx R650 manipulator. Figure 1 shows a picture of this robot and the used Denavit-Hartenberg (D-H) frames, while Tab. I reports the associated D-H parameters. Through the RSI software, the control unit of the KUKA KR5 returns (every 12 ms) only the absolute value of the motor currents, together with the joint position measures from the encoders. In this paper, however, we have considered a simulated version of this robot. Without loss of generality, we assumed to acquire directly the absolute value of the motor torques.

For our simulations, we have chosen a set of plausible dynamic parameters and generated the robot dynamic model in symbolic form using the Euler-Lagrange method. At the end of the procedure, we obtained 36 dynamic coefficients $\boldsymbol{\pi}_R$. The absolute values of the motor torques have been made available to the algorithm after the addition of noise.

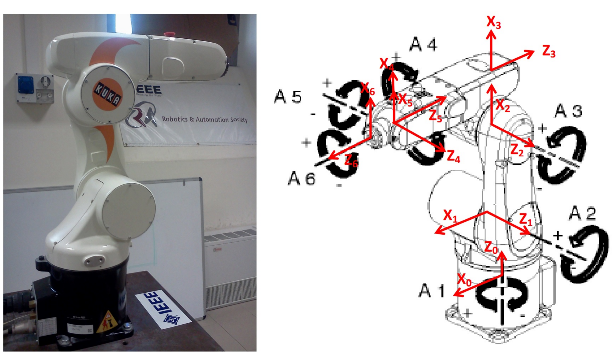

Fig. 1. The KUKA KR5 Sixx R650 (left) with the used D-H frames (right).

TABLE I
Denavit-Hartenberg parameters of the KUKA KR5 Sixx R650

i	a_i [m]	α_i [rad]	d_i [m]	θ_i [rad]
1	$a_1 = 0.075$	$-\pi/2$	$d_1 = 0.132$	$q_1 = 0$
2	$a_2 = 0.270$	0	0	$q_2 = -\pi/2$
3	$a_3 = 0.09$	$\pi/2$	0	$q_3 = 0$
4	0	$-\pi/2$	$d_4 = -0.295$	$q_4 = 0$
5	0	$\pi/2$	0	$q_5 = 0$
6	0	π	$d_6 = -0.08$	$q_6 = 0$

B. Numerical simulations

For the identification, we designed exciting trajectories as sums of multiple sine waves (different for each of the six joints), as described in [7]. These trajectories have been commanded during 13.33 s, collecting for each joint $M = 667$ samples of positions (for a total of 4002 samples), while the simulated motor torques $\boldsymbol{\tau}$ have been computed through the nominal inverse dynamic model (2). Figure 2 shows the actual motor torques τ_j, $j = 1, \ldots, 6$ (blue lines) and the downstream torques $\tau_{s,j} = |\tau_j + \epsilon|$ (red lines). Due to the presence of noise, the signals $\tau_{s,j}$ have been filtered (green lines) and used as inputs for the T-PBPR algorithm, together with the joint positions, velocities and accelerations. Furthermore, in order to properly isolate the torque segments, we discarded the samples close to zero (i.e., below a given threshold, different for each joint) resulting in a total of 2577 torque samples. Accordingly, we discarded the corresponding motion samples. Physical feasibility constraints have been supplied to the T-PBPR algorithm, together with suitable upper and lower bounds for each of the 60 dynamic parameters $\boldsymbol{p}$.

The number of chosen segments to be considered initially is $s_0 = 5$, resulting in 32 concurrent optimization problems to be solved during the first step of the T-PBPR algorithm. As a good trade-off between the computational effort and the reliability of the obtained results, we chose a branching factor $w = 5$ (see Algorithm 1), so as to deal with 10 optimization problems at each iteration. Figure 2 reports also the results of the torque signs estimation by the T-PBPR algorithm. Comparing the +/- signs of the identified $s = 39$ segments (highlighted with yellow strips) with the signs of the actual torques (blue lines), we observe that all the torque signs have been correctly estimated.

As a result of the T-PBPR algorithm, the most significant 27 estimated dynamic coefficients $\widehat{\boldsymbol{\pi}}_R$ (out of a total of 36), namely those coefficients with relative standard deviation below 25%, are reported in Tab. II, showing the effectiveness of the proposed method.

Finally, to validate the feasible dynamic parameters obtained from the T-PBPR algorithm, we have used the values $\widehat{\boldsymbol{p}}$ in a Newton-Euler routine to compute the robot motor torques along new validation trajectories. The result of this procedure is reported in Fig. 3, where the estimated torques are almost overlapping the nominal ones. This indicates also the robustness of the proposed method, which returns reliable estimations even in the presence of non-negligible noise affecting the torque signals.

V. Conclusions

We have presented an efficient method for identifying the dynamic coefficients of a robot equipped with motor current or joint torque sensors that return only the absolute value of the measured quantity. Classical OLS techniques do not provide reliable results in this case. Estimation of the correct signs of the torques can be obtained by the proposed T-PBPR algorithm that incrementally builds a tree of possible solutions, solves a reduced set of constrained optimization problems, and progressively discards the tree nodes leading to unfeasible parameters. The output of the complete algorithm includes the estimated torque signs during the analyzed motion, the

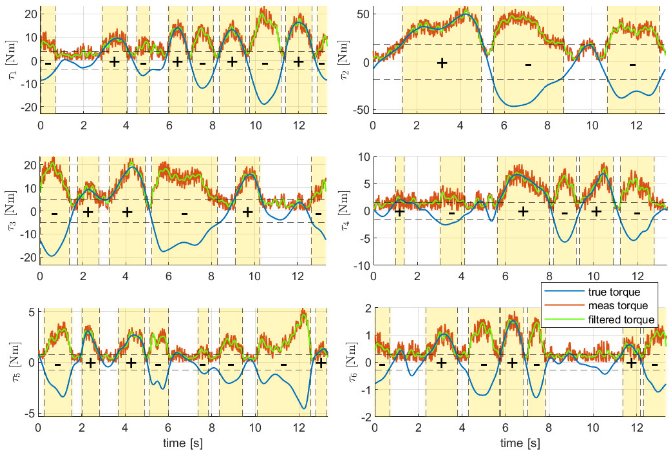

Fig. 2. Simulated torques for the KUKA KR5 robot during an exciting trajectory. The nominal torques (blue lines) are hidden to the user, while only their absolute values (with additional noise) are available as measures (red lines). These are filtered (green lines) before being used in the T-PBPR routine. The yellow strips highlight the detected segments, and the +/- symbols indicate the signs estimation obtained as a result of the T-PBPR algorithm.

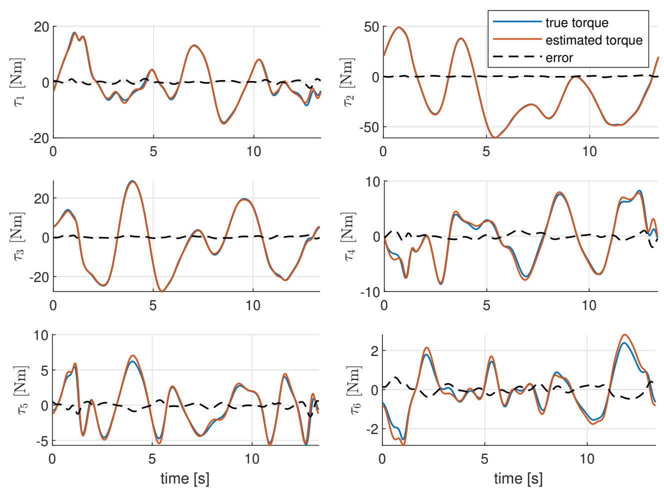

Fig. 3. Validation of the T-PBPR algorithm on a new trajectory. The nominal torques during robot motion (blue lines) are compared with the estimated torques obtained from a Newton-Euler routine (red lines), which employs the feasible set of dynamic parameters $\widehat{\boldsymbol{p}}$ returned by the T-PBPR algorithm. The estimation error (dashed black lines) is minimal.

estimated dynamic coefficients and a feasible set of dynamic parameters. As a result, the obtained dynamic model can be used for motion control laws based on inverse dynamics, both in Euler-Lagrange and in Newton-Euler formulations.

The method has been tested on a simulated version of a KUKA KR5 manipulator, obtaining very satisfactory results. A simulation study was necessary in order to effectively validate the proposed approach, since no ground truth measurement of motor currents or torques would be available on the real robot. We are currently working on the application of the T-PBPR algorithm to the KUKA KR5 Sixx manipulator available in our laboratory.

TABLE II

REAL ($\boldsymbol{\pi}_R$) AND ESTIMATED ($\widehat{\boldsymbol{\pi}}_R$) DYNAMIC COEFFICIENTS FOR THE SIMULATED KUKA KR5 ROBOT

Symbolic form $\boldsymbol{\pi}_R(\boldsymbol{p})$ of the dynamic coefficients	$\boldsymbol{\pi}_R$	$\widehat{\boldsymbol{\pi}}_R$
$J_{1yy}+J_{2yy}+J_{3zz}+a_1^2m_1+(a_1^2-a_2^2)m_2$ $+(a_1^2-a_2^2-a_3^2)(m_3+m_4+m_5+m_6)+2a_1c_{1x}m_1$	1.7961	1.8352
$J_{2xx}-J_{2yy}+a_2^2(m_2+m_3+m_4+m_5+m_6)$	1.0935	0.8926
$J_{3xx}-J_{3zz}+J_{4zz}+a_3^2m_3$ $+(d_4^2+a_3^2)(m_4+m_5+m_6)-2d_4c_{4y}m_4$	1.2425	1.1083
J_{3xz}	0.2000	0.2820
$J_{3yy}+J_{4zz}-a_3^2m_3$ $+(d_4^2-a_3^2)(m_4+m_5+m_6)-2d_4c_{4y}m_4$	2.0967	1.8308
J_{3yz}	0.2000	0.2154
$J_{4xx}-J_{4zz}+J_{5zz}$	0.5000	0.7674
$J_{4yy}+J_{5zz}$	1.5000	1.5438
$J_{5xx}+J_{6yy}-J_{5zz}+d_6^2m_6-2d_6c_{6z}m_6$	0.2040	0.1709
J_{5xy}	0.1000	0.1125
J_{5xz}	0.1000	0.0591
$J_{5yy}+J_{6yy}+d_6^2m_6-2d_6c_{6z}m_6$	0.7040	0.7745
J_{5yz}	0.1000	0.1003
$J_{6xx}-J_{6yy}$	0.0000	0.0497
J_{6xy}	0.0500	0.0614
J_{6xz}	0.0500	0.0596
J_{6yz}	0.0500	0.0361
J_{6zz}	0.2000	0.2298
$a_2(m_2+m_3+m_4+m_5+m_6)+c_{2x}m_2$	3.1500	3.1504
$c_{2y}m_2$	0.1200	0.1172
$a_3(m_3+m_4+m_5+m_6)+c_{3x}m_3$	0.4100	0.3966
$d_4(m_4+m_5+m_6)-c_{4y}m_4+c_{3z}m_3$	-1.1050	-1.1138
$c_{4x}m_4$	0.0900	0.1028
$c_{5y}m_5+c_{4z}m_4$	0.0900	0.0506
$d_6m_6+c_{5z}m_5-c_{6z}m_6$	-0.1200	-0.1160
$c_{6x}m_6$	0.0100	0.0248
$c_{6y}m_6$	-0.0100	-0.0178

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