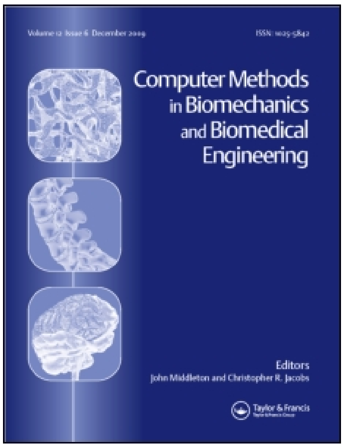

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A multi-platform comparison of efficient probabilistic methods in the prediction of total knee replacement mechanics

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A multi-platform comparison of efficient probabilistic methods in the prediction of total knee replacement mechanics

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Explicit finite element (FE) and multi-body dynamics (MBD) models have been developed to evaluate total knee replacement (TKR) mechanics as a complement to experimental methods. In conjunction with these models, probabilistic methods have been implemented to predict performance bounds and identify important parameters, subject to uncertainty in component alignment and experimental conditions. Probabilistic methods, such as advanced mean value (AMV) and response surface method (RSM), provide an efficient alternative to the gold standard Monte Carlo simulation technique (MCST). The objective of the current study was to benchmark models from three platforms (two FE and one MBD) using various probabilistic methods by predicting the influence of alignment variability and experimental parameters on TKR mechanics in simulated gait. Predicted kinematics envelopes were on average about 2.6 mm for tibial anterior–posterior translation, 2.9° for tibial internal–external rotation and 1.9 MPa for tibial peak contact pressure for the various platforms and methods. Based on this good agreement with the MCST, the efficient probabilistic techniques may prove useful in the fast evaluation of new implant designs, including considerations of uncertainty, e.g. misalignment.

Keywords: total knee replacement; kinematics; contact mechanics; knee mechanics; probabilistic methods; simulation

1. Introduction

Computational analysis has been used in orthopaedic studies since the 1980s (e.g. Huiskes and Chao 1983; Prendergast 1997). Modelling the behaviour of total knee replacements (TKRs) is challenging, as the stresses generated within the prosthesis and the supporting bone are a function of the kinematics, and the kinematics in turn are a function of the implant design, the relative position of the components and the balance of the soft tissues. Early studies used quasi-static loading conditions, effectively ignoring the influence of the dynamic kinematics of the joint. Recently, various researchers have adopted implicit (Otto et al. 2001) and explicit (Godest et al. 2002; Halloran et al. 2005a, 2005b) finite element (FE) or rigid-body (Fregly et al. 2003) modelling techniques to simultaneously predict kinematics and stresses.

Clinical and experimental simulator studies have reported substantial variability in TKR kinematics (DesJardins et al. 2000; Mahaluxmivala et al. 2001; Dennis et al. 2003; Zihlmann et al. 2005). This variability has considerable implications; e.g. for TKR wear (McEwen et al. 2001) and range of motion (Walker and Garg 1991). Computational models have shown good agreement with experimental simulator results (Godest et al. 2002; Halloran et al. 2005a, 2005b), providing important model validation as well as additional insight into performance metrics that are difficult to measure experimentally (like contact pressure (CP)). Although models are typically developed for 'average' conditions, they are an ideal platform to explore the influence of variability, as a consequence of either patient-, surgery- or component-related factors. Parametric studies have been performed to assess model sensitivity, but these studies have typically explored the influence of only one or two variables at a time (e.g. Li et al. 2001; Taylor and Barrett 2003; Besier et al. 2008; Elias et al. 2008). Probabilistic evaluations assess multiple parameters simultaneously and represent each input parameter as a distribution in order to predict an envelope of performance. In addition to accounting for potential interaction effects, the probabilistic approach predicts performance bounds and sensitivity factors for each input.

Probabilistic FE analyses have been applied to assess the structural reliability of orthopaedic components (Browne et al. 1999; Nicolella et al. 2001; Dar et al. 2002). More recently, the application of efficient probabilistic techniques has been used to assess the performance of TKR (Laz et al. 2006a, 2006b). The advanced mean value (AMV) method [corroborated with a 1000 trial Monte Carlo simulation technique (MCST)] assessed the impact of experimental variability in a knee wear simulator on predicted TKR mechanics by determining the performance envelopes of joint kinematics

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and contact parameters. In the Laz et al. (2006a) study, eight component alignment parameters and four experimental parameters were represented as Normal (Gaussian) distributions and used with probabilistic methods to assess the response of the TKR model.

A variety of software packages exist for FE, multibody dynamics (MBD) and probabilistic methods. This study seeks to evaluate whether model predictions would differ depending on the software platform used, to evaluate the robustness of the computational and probabilistic approach. The aims of this benchmark study are to perform probabilistic TKR mechanics predictions using three different platforms combining FE or MBD solvers with statistical/probabilistic analysis methods and so to evaluate the accuracy and efficiency of various platforms and probabilistic methods.

2. Methods

This study will evaluate performance envelopes for tibial anterior–posterior (AP) translation, tibial internal–external (IE) rotation and tibial peak contact pressure during a standard gait cycle using explicit FE and rigid-body modelling techniques and will compare results of the AMV and response surface methods (RSMs) to those from MCST.

2.1 *Deterministic modelling of the* in vitro *simulator*

In all three analyses, an isolated tibiofemoral joint was modelled (Figure 1). The loading conditions represented

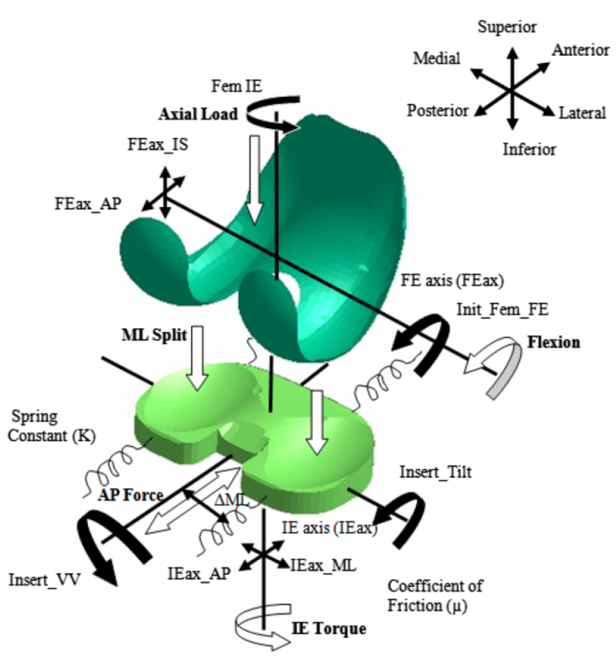

Figure 1. Probabilistic study parameters in the FE model of TKR. (For the definition of the abbreviations used, see Table 1.)

the force-controlled gait simulation of a knee wear simulator (Walker et al. 1997; DesJardins et al. 2000; ISO Standard 14243-1, 2002). Models were developed from digital geometry representations of semi-constrained, fixed-bearing, cruciate-retaining TKR. The distal surface of the tibial insert was supported in the inferior–superior (IS) direction, while loading conditions applied to the insert included an AP load and IE torque. An axial load was applied along the IS axis and the femoral flexion–extension angle was applied along an axis consistent with the experimental knee simulator.

Varus–valgus (VV) and tilt of the insert were both constrained. AP, medial–lateral (ML) and IE degrees of freedom (DOF) were unconstrained. The femoral component was constrained in IE, ML and AP DOF but unconstrained in VV and IS DOF and displacement-controlled flexion rotation was applied. Axial compressive force was also applied to the femoral component. The model included simulated soft-tissue constraint present in the knee simulator consisting of four springs constraining the insert AP displacement and IE rotation (Figure 1).

Three different analysis packages were investigated in order to build a baseline deterministic model, both to benchmark the results and to provide a platform for further stochastic modelling.

(1) Abaqus/Explicit: An explicit FE model of the TKR (Laz et al. 2006a) was developed in Abaqus/Explicit (Simulia, Providence, RI, USA). The tibial insert was represented with three-dimensional, eight-nodal hexahedral elements (~8500), and rigid triangular surface elements (~19,000) were used for the femoral component. A convergence study was implemented before the probabilistic analysis to confirm if the mesh density was acceptable (Halloran et al. 2005a). The femoral and tibial components were represented as rigid bodies, with a non-linear pressure–overclosure relationship (Halloran et al. 2005b).
(2) MSC ADAMS: The MBD model was developed in ADAMS (MSC Software Corporation, Santa Ana, CA, USA). The deterministic study principally involved modelling with the ADAMS/View module. In order to model contact, ADAMS uses an 'IMPACT' function, which relates normal reaction force to interpenetration displacement and can be used for extremely high-speed single-contact 'surrogate' models (e.g. Lin et al. 2009). However, if contact pressure information is required, then a unified single-body contact force is not adequate (as it does not include information about the force distribution), so instead the articulation must be 'discretised' into multiple contacts across the surface to estimate the local contact force contribution at each location. Various established penalty-based

algorithms exist for such a distributed contact model, for example, the elastic foundation model (Fregly et al. 2003).

(3) PAM-CRASH: An explicit FE model (Godest et al. 2002) was developed in PAM-CRASH (ESI/PAM System International, Rungis Cedex, France). Both the femoral component and the tibial polyethylene insert were modelled as rigid bodies using four-node shell elements. An advanced penalty based contact algorithm (contact element 44 in PAM-CRASH) was used to model the contact between the two components. This algorithm operates by penalising the geometric penetration of the slave nodes by counteracting forces proportional to the penetration depth of the tibia and a user-specified penalty factor.

2.2 Probabilistic modelling

Probabilistic modelling techniques are utilised to account for uncertainty in multiple input parameters and to predict a distribution of performance. In the present probabilistic evaluations, 12 experimental parameters (Table 1) representing component alignment, loading and experimental conditions were evaluated. The experimental parameters included four translations and four rotations of the femoral component and tibial insert. The rotations and translations defined the position of the femoral component and tibial insert relative to the fixed rotational axes (Figure 1). In addition, experimental set-up parameters (the spring stiffness constant, the ML separation of the springs and ML load split) and friction were also included. The levels of variability (Table 1) were estimated for a knee simulator with standard deviations of 0.5 mm for translational and 1° for rotational alignment (Laz et al. 2006a). Each of the parameters was assumed to be independent and normally distributed.

Table 1. Input factors for probabilistic study from (Laz et al. 2006a).

Parameter	MV	Variability σ
AP position of femoral FE axis (FEax_AP)	0 mm	0.5 mm
IS position of femoral FE axis (FEax_IS)	25.4 mm	
AP position of tibial IE axis (IEax_AP)	7.62 mm	
ML position of tibial IE axis (IEax_ML)	0 mm	
Initial femoral FE rotation (Init_Fem_FE)	0°	1°
Initial femoral IE rotation (Fem_IE)		
Tilt of the tibial insert (insert tilt)		
VV position of the tibial insert (insert_VV)		
ML position of spring fixation (ΔML)	28.7 mm	0.5 mm
Spring stiffness (K)	5.21 N/mm	0.09 N/mm
ML load split (60–40%) (ML_load)	60%	2.5%
Friction coefficient (μ)	0.04	0.01

Analyses were performed using three probabilistic methods (MCST, RSM and AMV) in three probabilistic platforms:

(1) Nessus/Abaqus: The Nessus probabilistic software (SwRI, San Antonio, TX, USA) was integrated with the FE model through custom scripting. The AMV and MCST methods were applied.

(2) Insight/ADAMS: The statistical analysis module Insight/ADAMS was used with the MBD solver. RSM and MCST methods were applied.

(3) PAM-OPT/PAM-CRASH: The optimisation software PAM-OPT was used in conjunction with the PAM-CRASH model. A 1000-trial MCST analysis was performed. Following this, a first-order RSM implemented in MATLAB (Mathworks, Inc., Natick, MA, USA) was implemented with a reduced set of MCST points (25, 50 and 100).

A brief description of the probabilistic methods utilised is included to highlight the differences in accuracy, efficiency and robustness. MCST involves repeated sampling of the input parameters according to their distributions, with the accuracy of the resulting output distribution dependent on the number of trials performed. The MCST is a robust method which provides accurate results with many trials, but is computationally expensive.

For RSM (Box and Wilson 1951), an analytic function of the input variables is fitted to approximate the output parameter over the sample space, based on an initial set of model evaluations. The initial set of model evaluations can be performed at random, but better results are achieved by distributing the trials regularly across the sample space. In the most basic case, a low-order polynomial and regression technique may be used to determine the term coefficients. Subsequently, MCST is performed using this response surface equation, instead of performing additional evaluations (resulting in lower computational cost). RSM works best when the output response is well represented by the analytic function, i.e. relatively linear, smooth and monotonic models; highly non-linear functions are not well represented. The higher the order of the response surface equation used, the more terms arise; hence, more samples are needed to achieve a good fit with the regression. Beyond second-order terms, this becomes impractical for many models. In the current study, the TKR model is expected to be relatively linear within the small perturbation range being studied here; accordingly, a first-order (linear) response surface equation was evaluated based on initial sample sizes of 25, 50 and 100 trials and subsequent MCST of 1000 evaluations of the response surface equation.

The AMV method is an optimisation-based method utilising a mean value (MV) approximation augmented with higher-order terms to determine the response at a specified probability level (Wu et al. 1990). Although an approximate technique, the AMV method has been shown to work well for well-behaved monotonic systems (Easley et al. 2007) and has been implemented in the prediction of performance envelopes for TKR (Laz et al. 2006a). The MV family of methods begins with a *local* first-order (linear) approximation of the function about the MV of the input function – whereas RSM builds a *global* model. The MV model is suitable for fairly linear problems but is not accurate for non-linear behaviour; its main practical use is as the basis for the subsequent AMV. The AMV method takes the linear model derived by the MV method and attempts to include corrective terms to approximate the higher-order effects. AMV takes the MV prediction and, using data from the calculated most-probable point (MPP) of interest, corrects this value for a single level of desired probability (or desired output), which gives the corrected AMV estimate of the output. The calculated MPP is the global maximum of the probability distribution function of all the possible different points of failure along a 'limit state' (i.e. failure) function. Essentially, the AMV gives a more accurate representation at one localised point of the possibility space, whereas RSM gives a less accurate representation, but is valid across the entire possibility space.

For each platform, the results of the combined probabilistic/mechanical modelling were a bounded response representing the 1st and 99th percentiles over the gait cycle for the performance metrics: AP translation, IE rotation and peak CP. AP translation and IE rotation are reported relative to the 'settled' reference positions of the components. Additionally, sensitivity factors, representing the effect of varying each input parameter on the output response, identify the most and least important parameters. With AMV, the sensitivities are computed in the standard normal variate space as the unit vector from the origin to the MPP and serve as relative indicators of the contributions of variability in the parameters to variability in each performance measure. In the PAM-OPT/PAM-CRASH and Insight/ADAMS studies, the sensitivities at each time point were calculated as the linear regression fit of the input variables ('normalised' based on standard deviations) to the reduced set of 25, 50 or 100 MCST points. The absolute magnitude of the sensitivity values at each time point was then averaged over the gait cycle to give a mean absolute value. To provide an overall indication of importance, the reported sensitivity factors are the normalised averaged absolute values over the gait cycle.

3. Results

3.1 Comparison of the deterministic results

The deterministic results for AP translation, IE rotation and peak CP showed good agreement between the Abaqus, ADAMS and PAM-CRASH platforms and with the experimental results (Figure 2). To quantify the differences between the different model results and the experimental data, the root mean square (RMS) variations over the gait cycle were computed between each model and the experimental data and between models (Table 2). RMS differences between model and experiment averaged 0.6 mm and 1.0° for AP translation and IE rotation, respectively. RMS differences between models were of a similar magnitude. While the general behaviour in predicted peak CP was similar for all models, there were differences in the predicted magnitude, mainly due to the difference in contact formulations between platforms.

Computation time for an analysis was approximately 3 min in Abaqus/Explicit (Intel Pentium 4 3 GHz, 2 Gb RAM), 4 min in PAM-CRASH (Intel Pentium 4 3.20 GHz, 2 Gb RAM) and 6 min in ADAMS (Intel Pentium 4 3 GHz, 2 Gb RAM). Notably, for all three platforms, the analysis time is sufficiently low to allow larger-scale probabilistic studies.

3.2 Comparison of the probabilistic results

Envelopes of the 1–99% bounds were predicted for the TKR performance measures using the three platforms: Nessus/Abaqus, Insight/ADAMS and PAM-OPT/PAM-CRASH. The MCST comparisons (Figure 3) showed good agreement with trend and performance envelope size for the various platforms. Similar behaviour was observed for the response surface and AMV methods (Figures 4 and 5).

The differences between the methods (MCST versus AMV and MCST versus RSM) for the average and the maximum bounds for the various platforms (Table 3) were within 5% for kinematics. On average, envelope sizes were about 2.6 mm for AP translation and 2.9° for IE rotation. For all platforms, the kinematic envelopes were larger during stance than during the swing phase; this can be attributed to a combination of implant conformity, joint loading and external simulator constraint. During the stance phase, the implant has greater conformity and is subjected to higher loads than in the swing phase; under such conditions, small changes in the alignment variables require large adjustments of the implant for the system to reach its lowest energy state. In the absence of high joint loads, the external spring constraint plays a greater role in stabilising the implant, reducing the effects of alignment variability on predicted kinematics in the swing phase.

Bounds of peak CP predictions from MCST were comparable between the platforms, with average envelope size being 1.4, 2.5 and 2.8 MPa for Nessus/Abaqus,

Table 2. RMS differences between the various platforms.

Deterministic comparison	AP translation (mm)	IE rotation (°)	Peak contact pressure (MPa)
Abaqus and experiment	0.5	0.9	N/A
ADAMS and experiment	0.8	1.3	N/A
PAM-CRASH and experiment	0.6	0.9	N/A
Average	0.6	1.0	
ADAMS and Abaqus	0.5	0.9	1.1
PAM-CRASH and Abaqus	0.6	0.9	2.1
ADAMS and PAM-CRASH	0.4	1.0	3.0
Average	0.5	0.9	2.1

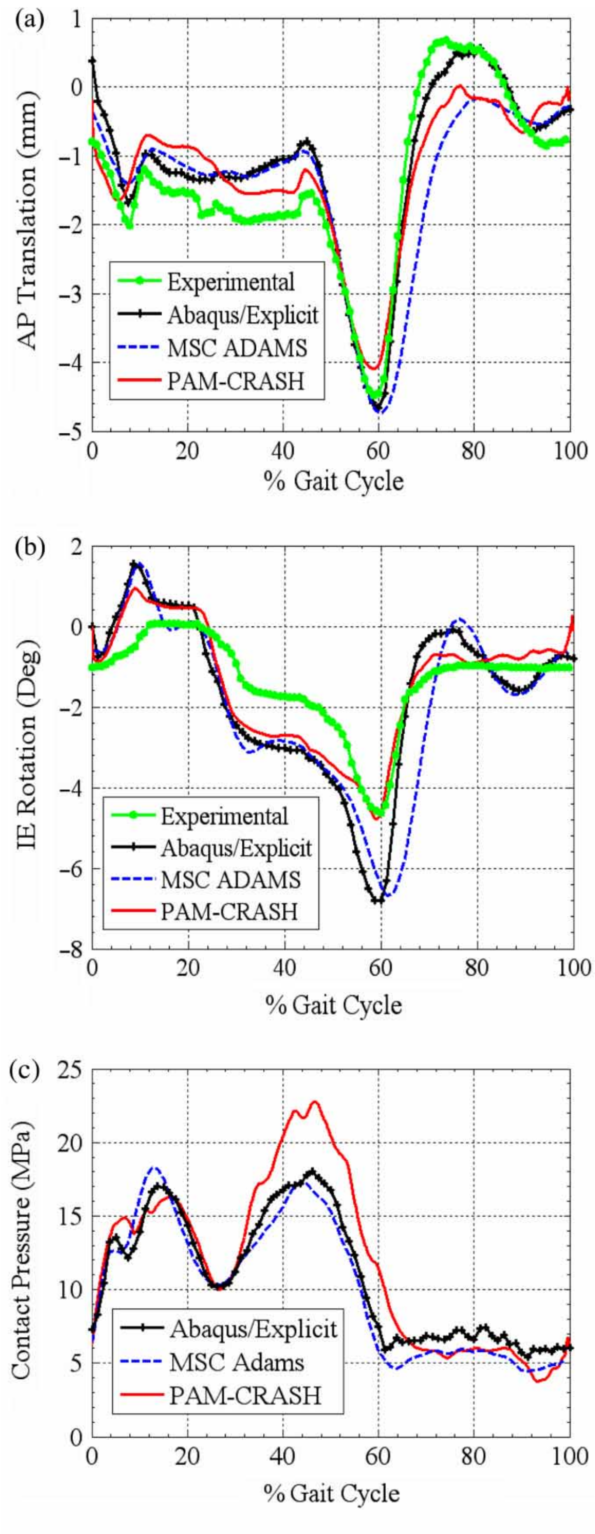

Figure 2. Tibial kinematics and tibial contact pressure from the three models: Abaqus/Explicit, MSC ADAMS and PAM-CRASH. (a) AP translation (+ anterior/− posterior), (b) IE rotation (+ external/− internal) and (c) peak contact pressure.

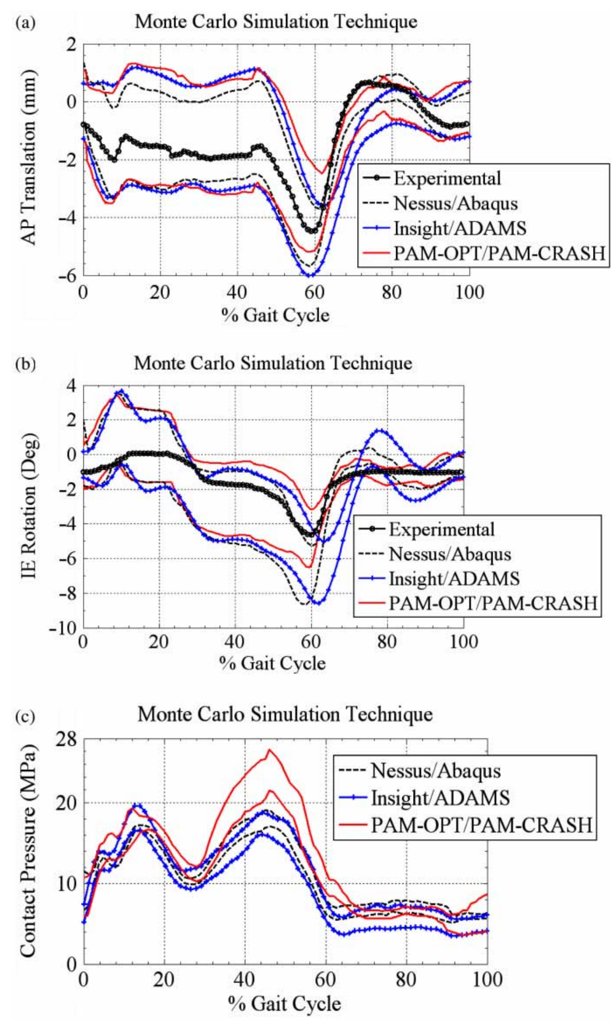

Figure 3. Comparison of predicted envelopes (1–99%) from MCST implemented in Nessus/Abaqus, Insight/ADAMS and PAM-OPT/PAM-CRASH. (a) AP translation (+ anterior/ − posterior), (b) IE rotation (+ external/− internal) and (c) peak contact pressure.

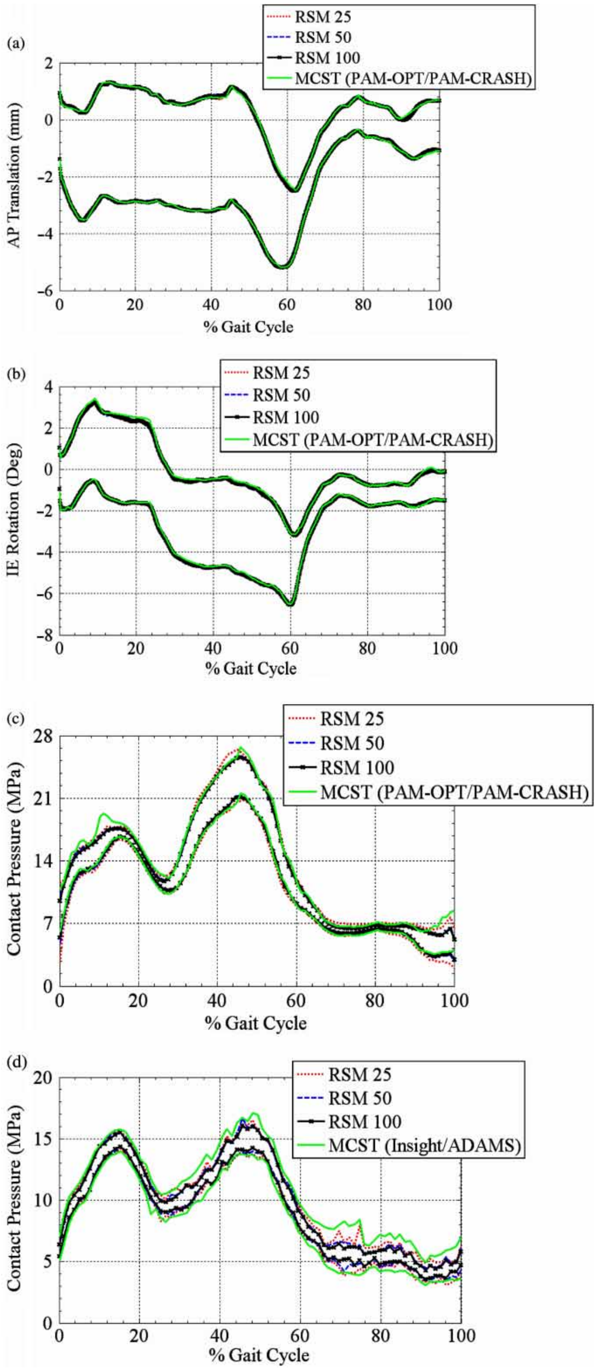

Figure 4. Comparison of predicted envelopes (1–99%) for RSM based on 25, 50 and 100 trials and MCST (solid line) with 1000 trials. Results from PAM-OPT/PAM-CRASH for (a) AP translation (+ anterior/− posterior), (b) IE rotation (+ external/− internal) and (c) peak contact pressure and from Insight/ADAMS for (d) peak contact pressure.

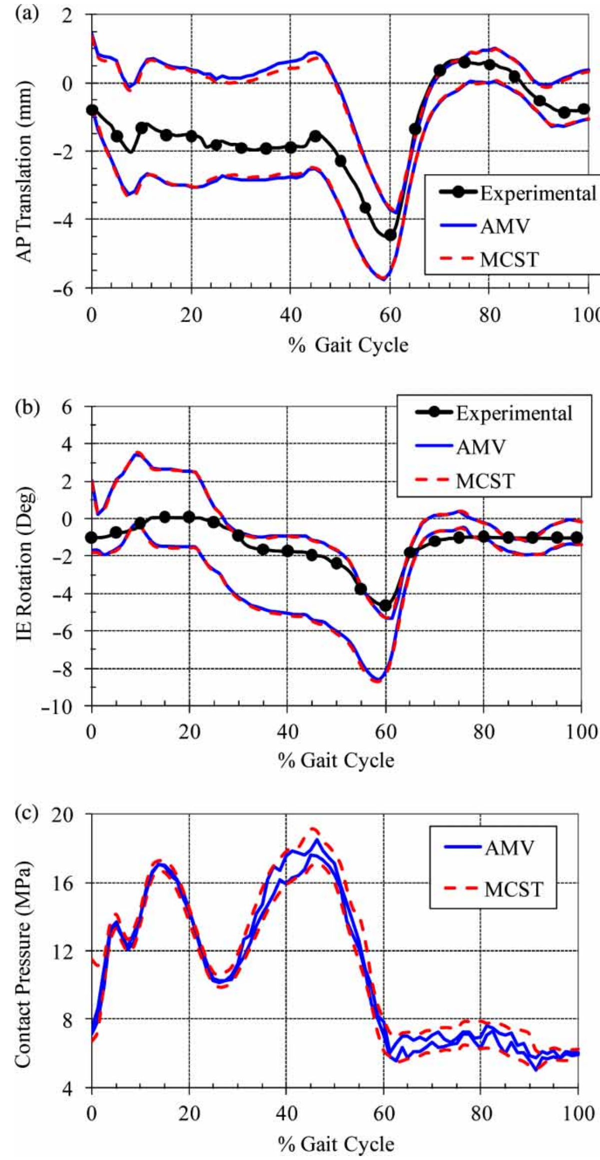

Figure 5. Comparison of predicted envelopes (1–99%) for AMV and MCST with 1000 trials using the Nessus/Abaqus platform. (a) AP translation (+ anterior/− posterior), (b) IE rotation (+ external/− internal) and (c) peak contact pressure.

Insight/ADAMS and PAM-OPT/PAM-CRASH platforms, respectively (Figure 3(c)).

Greater differences were observed in peak CP than in the kinematic measures, with largest RMS difference being up to 3.0 MPa between ADAMS and PAM-CRASH platforms (Figure 2(c)). It is difficult to acquire CP data from the experimental simulator under dynamic gait loading conditions; this underscores the need for modelling. This study was based on a previously verified FE model in Abaqus (Halloran et al. 2005a). Differences in predicted CP magnitudes were minimal between the two FE platforms, while greater differences observed from PAM-CRASH may be a result of a different rigid-body contact formulation implemented in this platform.

The RSM was evaluated to characterise the sensitivity of the response surface equation to the number of initial trials, specifically 25, 50 and 100 trials using PAM-OPT/PAM-CRASH and Insight/ADAMS platforms

Table 3. Comparison of average and maximum ranges of predicted 1 and 99 percentile bounds for the various performance metrics and platforms.

Measure/platform	AP translation (mm), Ave/Max	IE rotation (°), Ave/Max	Peak contact pressure (MPa) Ave/Max
Nessus/Abaqus			
MCST (1000 trials)	2.2/3.4	2.8/4.5	1.4/4.8
AMV	2.3/3.4	2.7/4.3	0.5/1.7
ADAMS/Insight			
MCST (1000 trials)	2.7/4.1	3.1/4.4	2.5/3.7
RSM (50 trials)	2.7/4.0	3.1/4.5	1.8/3.4
PAM-OPT/PAM-CRASH			
MCST (1000 trials)	2.9/4.1	2.8/4.5	2.8/6.2
RSM (50 trials)	2.8/4.1	2.8/4.5	2.4/5.7

(Figure 4). The kinematic (AP and IE) results for PAM-OPT/PAM-CRASH showed agreement between all RSM models and the MCST results, implying that an RSM based on 25 trials was sufficient. However, the RSM predictions of peak CP were more sensitive to the number of trials used. While good agreement could be achieved with PAM-OPT/PAM-CRASH for the maximum value of peak CP over the gait cycle using the 100-trial RSM, the secondary peak at 10% gait and the lower swing phase pressures were not well captured (Figure 4(c)). For the Insight/ADAMS platform, similar RSM results were observed where 25 trials were sufficient to characterise model kinematics (Table 3), but 100 trials were not sufficient to characterise the swing phase (Figure 4(d)). Similar results were observed for the AMV method (Figure 5, Table 3), where maximum differences in the size of the predicted AP and IE ranges were 0.07 mm and 0.18° for the AMV and MCST methods, respectively. As contact pressure during swing phase exhibited more non-linear behaviour, approximate methods such as RSM and AMV were less accurate (Figures 4 and 5). Regarding computation time, MCST (1000 trials) ranged from 50 to 100 h, AMV results for a single performance measure (173 trials) required ~9 h, RSM (25 trials) required 2 h and RSM (100 trials) required 8 h.

The sensitivities, reported as average of the absolute values over the gait cycle (Figure 6), illustrated the relative impact of the parameters on AP translation, IE rotation and peak CP. For AP translation and IE rotation, good agreement with important parameters and their magnitudes was obtained with the three software platforms. Insert tilt and femoral IE alignment were the most important parameters affecting AP translation and IE rotation, respectively. The sensitivity factors for peak CP identified four contributing parameters with relatively equal contributions: initial femoral flexion–extension, femoral IE, insert tilt and VV alignment.

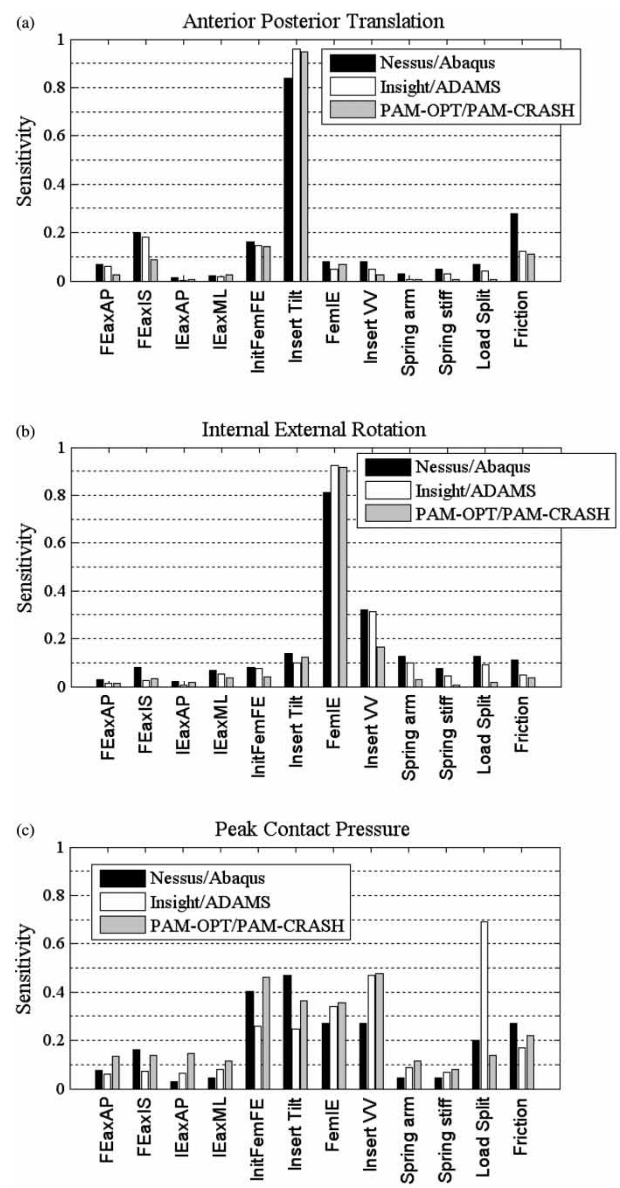

Figure 6. Sensitivity results for the various platforms represented by the averaged absolute values over the gait cycle for: (a) AP translation (+ anterior/− posterior), (b) IE rotation (+ external/− internal) and (c) peak contact pressure.

4. Discussion

In this benchmarking study, predictions of TKR performance under simulated gait conditions were performed with three FE/MBD platforms using different probabilistic methods. By comparing the results from the various platforms, this study evaluated whether the choice of computational platform affected the predicted results, as well as the accuracy and efficiency of the MCST, RSM and AMV probabilistic methods.

Notably, the deterministic results for AP translation, IE rotation and peak CP obtained using FE and MBD software platforms showed similar patterns throughout the gait cycle and were in close agreement with experimental kinematic data and between platforms (Figure 2). The RMS differences between the models were on average 0.5 mm for AP translation and 0.9° for IE rotation. Greater differences were observed in peak CP than in the kinematic measures, with RMS difference being up to 2.1 MPa between PAM-CRASH and Abaqus. The biggest difference was between ADAMS and PAM-CRASH of 3.0 MPa. Differences in the magnitude of CP were attributed to the different software platforms and the methods of implementing contact in a rigid-body simulation. Factors that are complicit in these differences include the contact model parameters, the frictional parameters and the effects of inertia within the model configurations. Nonetheless, in spite of these small differences, overall the trends and magnitudes of the responses matched favourably.

Supported by the accuracy of the deterministic results and fast computational times, probabilistic analyses were performed using three platforms: Nessus/Abaqus, Insight/-ADAMS and PAM-OPT/PAM-CRASH. MCST was carried out for all models and predicted that similarly sized performance envelopes were obtained for the kinematics in all three methods. Larger differences were observed in the 1 and 99% envelopes for peak CP, but these are again attributed to deterministic model differences rather than probabilistic methods. MCST computational times were similar for the three different platforms.

The increased computational times associated with probabilistic FE/MBD modelling represent an important barrier to incorporate such techniques in the design-phase evaluation of TKR implants. For example, the 1000-trial MCST implemented in PAM-CRASH/PAM-OPT required 4 days of computational time. This highlights the need to implement and validate more efficient alternatives to the 'gold standard' of MCST. Comparison of RSM envelope sizes to MCST yielded an average difference of 0.08 mm (2.9%) and 0.03° (1.0%) in AP translation and IE rotation, respectively (Figure 4(a),(b), Table 3), and computational costs substantially reduced to 4 h for the 50-trial RSM analysis. Similarly, comparison of AMV envelopes to MCST in Nessus/Abaqus yielded an average difference of 0.08 mm (3.7%) and 0.1° (3.6%) in AP translation and IE rotation, respectively (Figure 5, Table 3). The computational time required for the AMV analyses was ~9 h. It is important to note that the RSM and AMV methods are less robust for highly non-linear or non-monotonic systems. This explains the greater differences in CP results during the swing phase (Figures 4(c),(d) and 5(c)), when minimal constraint (due to small joint loads) resulted in a more non-linear system.

The efficient RSM and AMV methods provide distinct advantages compared to one another. The AMV method provides *local* approximation of system behaviour at pre-defined points in the possibility space, while RSM presents a *global* approximation across the entire possibility space. The RSM is less accurate than AMV at targeted local design point(s), but is more flexible than AMV in predicting behaviour across the entire possibility space. An RSM analysis requires a fixed number of trials regardless of the number of desired output measures; in contrast, an AMV analysis requires an additional trial for every desired output measure (e.g. AP translation, IE rotation or CP) and probability level (e.g. 1 or 99%).

As such, when implementing probabilistic methods to a new system whose response may be unknown, it is prudent to initially verify the outputs of the efficient AMV or RSM methods with an MCST simulation.

Independent of platform, the sensitivity factors identified the same set of important input parameters (Figure 6). Specifically, insert tilt was the greatest contributor to AP translation, while femoral IE alignment had the largest sensitivity factor for IE rotation. In addition to insert tilt and femoral IE alignment, two other alignment parameters were important to contact pressure: the VV position of the tibial insert and the initial femoral FE rotation.

These factors have been identified in clinical studies (Anouchi et al. 1993; Catani et al. 2006) and underscore the importance of component alignment to TKR mechanics (Dorr and Boiardo 1986).

In conclusion, this study performed benchmark comparisons of FE and MBD as well as probabilistic software packages and generally found good agreement between results independent of the modelling environment. Our results suggest that researchers can use both FE- and MBD-based approaches and probabilistic methods besides MCST with confidence that the results will be comparable across different platforms. The accuracy of the efficient probabilistic methods, e.g. RSM and AMV, can aid in the quicker design phase evaluation of the robustness of TKR implants to surgical and environmental variables.

Notes

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