

3 **Holistic approaches to pre-clinical TKR analysis: computationally-enriched**
4 **experimental testing**

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12 **SYNOPSIS**

13 The drive for better TKR designs necessitates better understanding of TKR mechanics through pre-
14 clinical analysis methods. Currently, corroboration between *in-silico* and *in-vitro* testing methods is
15 limited, and the opportunity for collaboration is underexploited. Here we demonstrate how *in-silico*
16 and *in-vitro* testing methods can be complementary and mutually supportive. The case study is a
17 corroboration of the AMTI knee simulator (displacement & force control) including control-plant
18 modelling, *in-silico* wear prediction and probabilistics. We demonstrate that more rigorous
19 *corroboration* between numerical & experimental techniques can benefit both approaches, and
20 ultimately provide much richer data for pre-clinical analysis; *however*, to be effective this requires
21 close and open *collaboration* between different research specialists. Only by working together to
22 share information and ideas more effectively can the next major advances in our understanding of
23 TKR be achieved.

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26 **1. INTRODUCTION**

27 Considerable work goes into pre-clinical analysis of TKR designs, to refine them as much as possible
28 before time-consuming costly clinical trials. Historically, individual research groups specialised either
29 in computational or experimental approaches. These have provided valuable insights into TKR
30 performance, but are limited in scope. Whilst many *in-silico* studies are based on experimental data
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1 (e.g. [1, 2]), the degree of interaction is often limited. The need exists to establish better
2 collaborative links between theoretical, experimental, and computational modelling methods. This
3 demonstrates not only that test results are repeatable and consistent, but also that the underlying
4 physics of the test conditions are correctly and fully understood.

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7 **2. METHODS**

8 This paper focuses on an exploratory review of the AMTI knee wear simulator, operating under both
9 displacement & force control, based on closer corroboration between experimental & computational
10 methods. Rigid-body models were created using MSC.ADAMS [3-5]. These models were modified to
11 reflect the configuration of the AMTI simulator assembly (including the full tibial platen and
12 associated bearings). Further, a full control-plant model was implemented in MATLAB/Simulink, and
13 finally the model was fully parameterised to facilitate probabilistic modelling. Tests were
14 corroborated for different gait profiles with fixed-bearing PCL-retaining implants.

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16 For *displacement-driven* models kinematic-feedback data from individual tests was used directly, so
17 a control plant was not required. *In-silico* force & torque predictions were compared to experimental
18 load-cell feedback. For *force-driven* tests a model of both the plant mechanics *and* control system
19 was used, to more fully model the system. Simple ‘isolation profiles’ were used to explore dynamic
20 effects (inertia, friction & damping) on each of the different axes individually. This was followed by
21 corroboration of force-driven gait tests.

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23 Wear was predicted *in-silico* using a number of standard algorithms, including Archard wear [6],
24 A/A+B ‘cross-shear’ wear [7] and crossing-intensity wear [8]. Wear models were considered with and
25 without contact-pressure terms. The results were also decomposed to explore individual wear
26 influences (sliding distance, cross-shear maps & contact pressures), to reveal which factors seemed
27 to correlate best with experimental data.

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29 Studies were not merely deterministic: probabilistic methods were also used to model experimental
30 variability (similar to [9]), *and* further to corroborate this with statistical data from multiple wear
31 tests. This is believed to be the first time probabilistic results for TKR have been corroborated against
32 experimental data.

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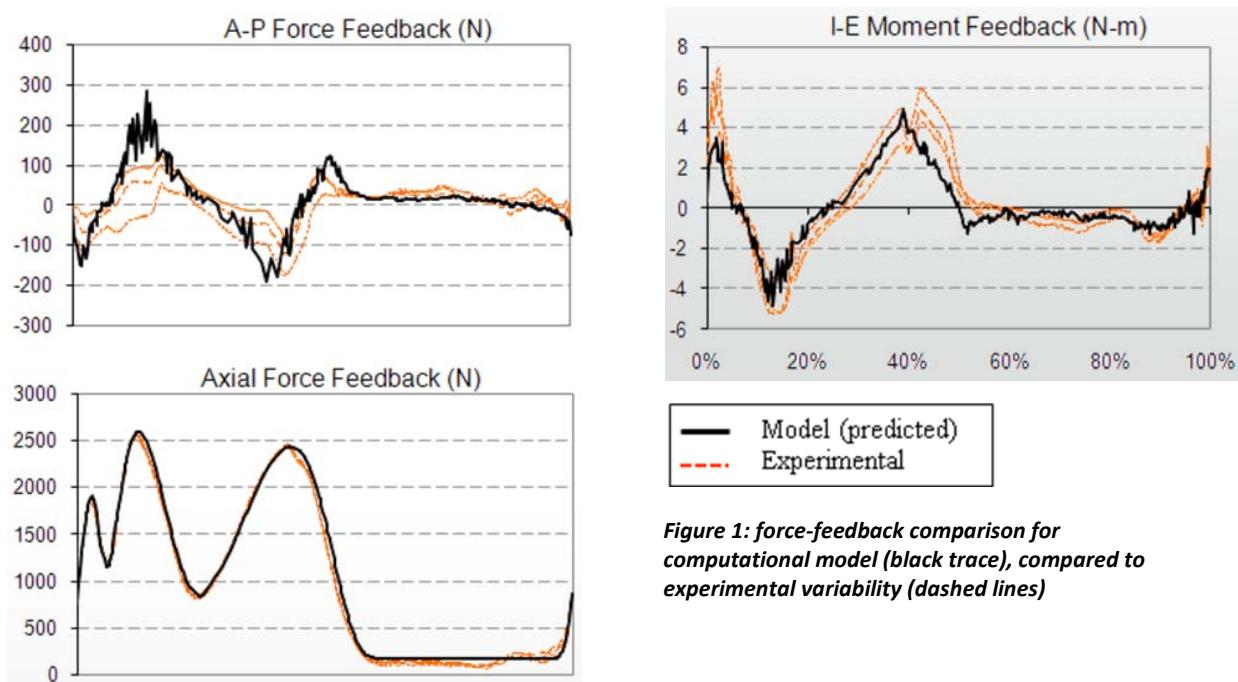
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1 3. RESULTS AND DISCUSSION

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3 The displacement-driven tests corroborated well, closely matching force-feedback *once test-specific*
4 *variables were tuned* (e.g. AP-dwell position, bearing friction). The results reveal the sensitivity of the
5 model to these variables (e.g. deviations of only 1mm in AP-dwell alter the AP axis force-feedback by
6 as much as $\pm 100\%$). These tests also show the importance of accurately modelling friction not just at
7 the implant articulation, but also the other bearings in the mechanical rig. *If* experimental conditions
8 are correctly accounted for, the *in-silico* results lie well within experimental variation ranges [figure
9 1].

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15 Force-controlled simulation proved more challenging; a simple 'quasi-static' mechanical model could
16 *not* adequately describe the system – the dynamics are highly influential. The influence of friction (of
17 the implant and other bearings) and damping in the system is considerable, and must be accounted
18 for. The role of inertia is relatively limited. Because the mechanical system sits within a control loop
19 the demanded and achieved waveforms will not perfectly match. Further, due to inertial and
20 damping elements between the actuator application point and the load cells, it is *not* adequate to
21 use force-feedback. Rather, the demanded inputs should be used with a control system (the
22 achieved feedback can be used to corroborate this control system). Corroboration of the 'isolation

Figure 1: force-feedback comparison for computational model (black trace), compared to experimental variability (dashed lines)

1 tests' has been successful in predicting output kinematics and load-cell feedback. However
2 discrepancies remain for the full gait test; these are believed to be related to further uncharacterised
3 system dynamics and the influence of pliancy in the fixed axes [10], on the tibial as well as the
4 femoral side.

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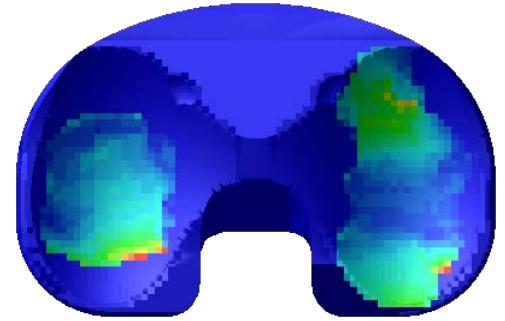
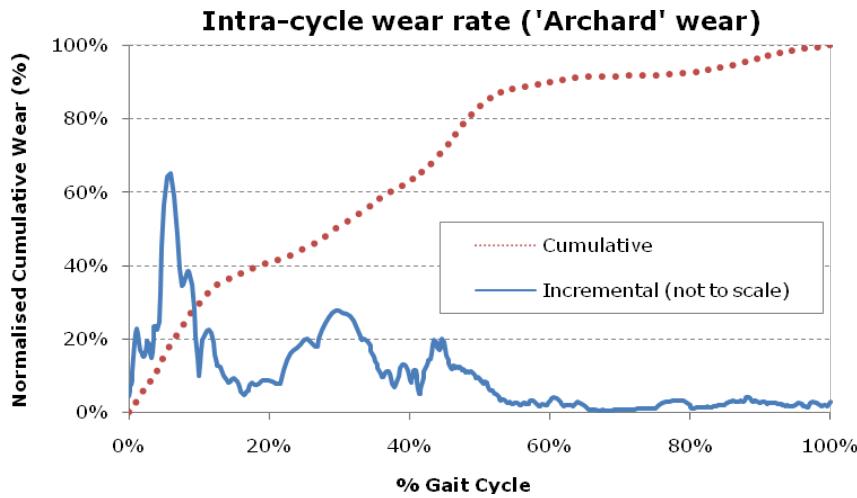
6 Wear results demonstrate that (whilst not quantitatively precise) current *in-silico* algorithms provide
7 a useful qualitative 'ranking' tool for TKR wear. *In-silico* methods can provide a richer diagnostic data
8 set than *in-vitro* tests alone (e.g. surface maps and probability distribution functions for cross-shear,
9 sliding distance & contact pressure [figure 2]). This is valuable for designers, clinicians &
10 theoreticians trying to better understand the causal influences of wear.

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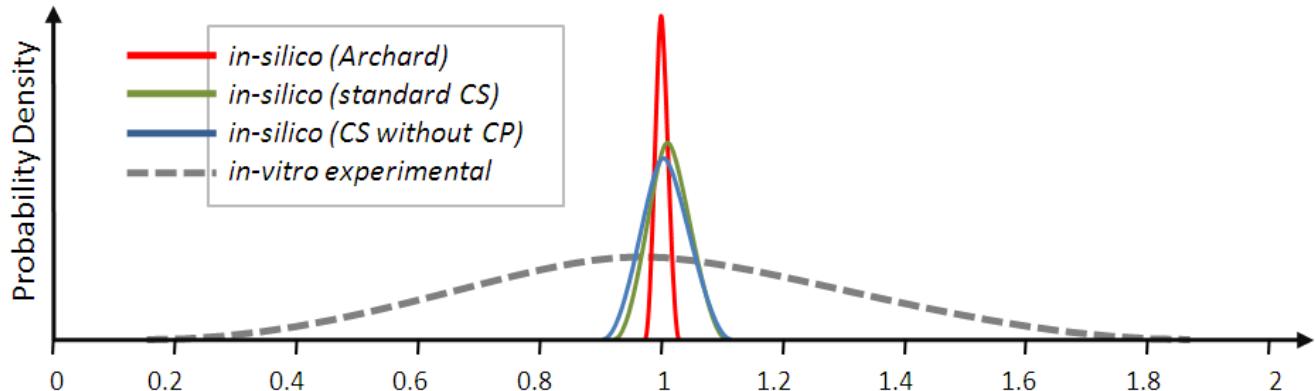


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Figure 2: examples of *in-silico* visualisations: cross-shear maps (above) & intra-cycle wear rate plots (left)

In addition to this, *corroborated* probabilistic studies provide additional insight into wear characteristics. By comparing the distributions for experimental and predicted wear, it is possible to compare the performance of different theoretical wear algorithms against *in-vitro* data [figure 3]. Note that it is very clear from this probabilistic vantage-point that current wear algorithms are not ideal. They are able to match the 'mean' deterministic value for wear rate (with appropriate tuning of the wear constant). However, they are *not* accurately capturing the 'spread' of wear rates based

1 on variations in the experimental set-up. This clearly shows further work is needed to better
2 understand the mechanics of wear, and also the factors influencing test variability.
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8 **Figure 3: using probabilistics to compare wear rate PDFs; all existing models drastically under-predict the full range**
9 **of experimental variability.**

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13 Conventionally, numerical models are ‘validated’ using experimental results, and the AMTI simulator
14 has been a popular target for this (e.g. [10, 11]). The present work advances this practice by
15 rigorously corroborating the system dynamics, controller behaviour & experimental variability- not
16 just the most basic mechanics. It is apparent that these test rigs are more complex than older models
17 have assumed, and artefacts of the rig construction and dynamics are influencing results. In the past,
18 a ‘first-approximation’ was adequate to lay the foundation for theories of knee mechanics and wear,
19 but we now require a more detailed appreciation of these tests if we are to further our theories of
20 wear. Specifically, researchers testing with the AMTI simulator are advised to pay particular
21 attention to the AP-dwell position, and the degree of friction from the roller bearing assembly. An
22 advantage here of computational modelling is that it can be used *post-hoc* to further investigate
23 anomalous *in-vitro* test outcomes or sensitivity to experimental uncertainty.

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25 Considering the wear algorithms, we know that these empirical models are imperfect [4]; however
26 they represent the state-of-the-art, and to advance further, more accurate corroboration is required.
27 Accounting for discrepancies between *in-silico* and *in-vitro* tests (especially using probabilistic
28 methods) can provide valuable insights into the underlying factors involved in wear.

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2 In conclusion, closer collaboration on these tests has lead to a better-understanding of the existing
3 experimental data, along with more accurate and powerful computational models. As a result,
4 advances have been made in our fundamental understanding of wear simulator mechanics.
5 Researchers in all fields of TKR testing are strongly encouraged to engage in closer collaboration
6 across disciplines, to more provide a better, richer and more rigorous toolset for pre-clinical analysis.
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8 *Acknowledgements: Research has been supported by the EPSRC and DePuy, A Johnson & Johnson
9 Company.*

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11 References: [1] Godest et al, 2002 J. Biomech 35(2). [2] Knight et al, 2007, J. Biomech 40(7). [3]
12 Strickland et al, 2007, Trans 53rd ORS. [4] Strickland et al, 2008 Trans 54th ORS. [5] Arsene et al,
13 2008, Trans 8th Symp CMBBE. [6] Archard, 1953, J.Appl Phys 24(8). [7] Turell et al, 2003, Wear
14 255(7-12). [8] Hamilton et al, 2005, J. Tribology 127(2). [9] Laz et al, 2006, J. Biomech 39(12). [10]
15 Lanovaz et al, 2008 Proc IMechE H 222(5). [11] Zhao et al 2006, ASME SBC.
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