GOLF CROQUET GRADING POSSIBILITIES

by

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This document provides an overview of fact finding done by the WCF Golf Croquet Ranking Committee in preparation for its recommendations (to come in a separate document). Hopefully, it will at the same time be instructive to the general croquet public, not merely to gain a better understanding of grading systems in general, but also of the particular grading problems that have arisen in the Golf Croquet situation.

A corresponding fact-finding document of the AC Ranking Review Committee, “Introduction to Dynamic Grading” served as a useful source of background information. We will refer to it as [ITDG] (see http://www.oxfordcroquet.com/tech/nel-dg/index.asp). We use the term ‘grading system’ as defined there: it departs from start grades assigned to the players and uses grade adjustments made in the light of new game results so as to maintain grades whose differences reflect win probabilities.

At the outset there was some hope that we might arrive at a reasonable recommendation by merely adapting the findings reported in [ITDG] in an appropriate way. Indeed, our original marching orders anticipated a report within a few months. It became clear that this expectation was unrealistic. The Golf Croquet situation differs significantly from that of Association Croquet, as will become clear. Furthermore, we had at the outset merely 60 thousand GC game results at our disposal – far less than what is needed for properly understanding long term effects. At the time when [ITDG] was written it was generally believed that a grading system need only be tested on one reasonably large set of games -- that it would behave in much the same way on other similar batches of games. This assumption turned out to be too optimistic: a considerable performance fluctuation from one batch of games to another was observed. To find out what causes this fluctuation was challenging. Our deliberations led to the discovery that future behavior of any grading system is very strongly influenced by the new start grades that repeatedly become added – something over which the grading system has no control. Ranking officers are in fact faced with a far more difficult task than had been realized until now. So, towards facilitating the task of future ranking officers, we put considerable effort into development of a method for automatic retrospective improvement of start grades.

Here follows a quick guide to noteworthy topics in the present document.

- (i) Best of 19 point games are treated differently to best of 13 point games. This is because the probability of the better player winning a longer game is higher. See section 2.
- (ii) Fixed modulator grading systems form the basic ingredient of all grading systems under consideration. We recall this concept and its basic features in section 3. The system currently used for world rankings is recalled in section 4 for convenient future reference.
- (iii) The Grade Deviation statistic allows objective comparison of grading accuracy. It is outlined in section 5 and described in detail in the Appendix.
- (iv) We discovered an ongoing decline over time in the grading accuracy of the current system as well as other traditional systems. See section 6.
- (v) We diagnose inaccurate start grades as main cause for the mentioned decline in grading accuracy and we develop a method for automatic revision of start grades. See sections 7 and 8.
- (vi) We introduce a new method to detect rapid improvers and also a new way to enable the grading system to keep their grades up to date, thus leading to improved dynamic grading systems. See section 9.
- (vii) We introduce an algorithmic method for classifying an event as being of Class 1. When this is combined with the improved dynamic grading, it leads to another good grading system. See section 9.
- (viii) The current system sometimes performs counter-intuitive grade adjustments. We examine the frequency of such adjustments and produce experimental results that shed light on circumstances that allow grade-smoothing to improve grading accuracy. See section 10.
- (ix) We examine how the performance statistics of various systems changed over very recent game results which had no influence on the design of the systems. See section 11.
- (x) We do a statistical comparison of recent ranking lists to see how a difference in grading accuracy translates into ranking difference. See section 12.

1. Data used.

Until otherwise stated, the calculations presented in this document are based on the data as they were on 14 March 2017, provided by the Ranking Officer. This was an update of similar data provided at various earlier stages. The data consists of a list of players and their start grades, a list of events with their classifications and a list of submitted game results, some of which have scores. The latter list can be subdivided as follows.

Games with win score = 7	131145
Games with win score > 7	5317
Games with win score < 7	2630
Games without scores	21516
Total games	160608

2. Win probabilities and best-of-19-hoop games.

The following fact is central to what follows. Given grades g_1 and g_2 for players P_1 and P_2, the Classical Win Probability formula estimates the Win Probability of P_1 over P_2 in the next game they play as follows:

(1.1) CWP(g_1,g_2) = 1/(1+10^((g_2 – g_1)/500))

The number 500 that appears here is an arbitrary choice, made once and for all. It determines, for every given grade difference, what win probability is represented. (If it is changed from 500 to 50 then it would still work, but a grade difference of 20 will then give the win probability of a grade difference of 200 when 500 is used).

In Golf Croquet, the ranking games are mostly bo13 games (= best-of-13 hoops) and formula (1.1) is used for such games. About 3% of games are classified as bo19 (= best-of-19 hoops). For games of the latter kind, the formula (1.1) would under-estimate the win probability of the higher graded player and thus over-estimate that of the opponent. In all calculations to follow in this document, except where explicitly noted otherwise, we are using the modified formula

(1.1a) CWP(g_1,g_2) = 1/(1+10^((g_2 – g_1)/Sc19)))

for win probability calculation in case of nominally bo19 games: thus the value 500 becomes replaced by a different value Sc19 (Scale 19) that has to be determined. It is possible to derive a theoretical value for Sc19 under the following assumptions:

Assumption 1. The separate hoop contests that comprise a GC game are independent events.
Assumption 2. Every game is either bo13 or bo19.

There is a well-known algebraic formula that expresses best-of-N win probability in terms of best-of-1 win probability when Assumption 1 is valid. The numerically calculated inverse provides the means to derive bo1 win probability from a known bo13 win probability. Then the mentioned algebraic formula allows computation of bo19 win probability from the bo1 win probability via Assumption 2. The theoretical value Sc19 = 408.5 is obtained along these lines. However, since both Assumptions are at best only approximately valid, the use of this theoretical value is not quite satisfactory. We deemed the games with win score > 7 to be bo19 and all other games to be bo13. Optional game scores are the only indication of whether a game is bo19 or not. We proceeded by using the value Sc19 = 450 as a reasonable estimate: it is somewhere between the bo13 scale parameter of 500 and the idealized theoretical value 408.5. Since it is applied in only about 3% of games, it fortunately has relatively small influence. However, it has enough influence for us to verify experimentally that 450 is better to use than either 408.5 or 500.

When Sc19 is below 500, the higher graded player in a bo19 game gets an appropriately larger win probability than formula (1.1) would have given. Accordingly, for all grading systems under consideration, a higher graded winner in a bo19 game gets a smaller grade increase than formula (1.1) would have given and, accordingly, a lower graded winner gets a larger increase.

3. Fixed Modulator Grading Systems.

A simple grading system can be obtained by defining the post-game **Grade Adjustment Algorithm** in terms of a fixed positive constant, the **Modulator**, as follows

(FM) New Grade = Old Grade + Modulator * (OW – EW), where OW = 1 for a winner, OW = 0 for a loser and where EW (=Expected Win) represents the win probability of the player. The algorithm (FM) amounts to the following:

Winner's New Grade = Winners Old Grade + Modulator * LWP,
Loser's New Grade = Loser's Old Grade – Modulator * LWP,

where LWP = Loser's Win Probability. This algorithm (FM) becomes a grading system when a particular value is assigned to the Modulator. For example, the assignment Modulator = gives us a **Fixed Modulator Grading system**.

The algorithm (FM) forms the basis of every grading system under consideration, as will be seen. Its updates cannot always result in a more accurate grade. For when a grade is an over-estimate and the player wins a game (which often happens), the postgame adjustment necessarily makes the grade even more over-estimated immediately after the game than it was before the game. Given this reality, a fixed modulator grading system (and systems derived from it) can at best produce grades that are collectively approximately correct. Our belief that the systems obtained can nevertheless be useful is not based on theoretical considerations. It is based on statistical evidence that we describe in section 5.

4. Continuous Grading and the system CSQ.

The Continuous Grading system currently in use is derived from the fixed modulator system that has Modulator = 50. In Continuous Grading this modulator is called the Index and it is cast in the role of a preliminary grade. The actual Grade is defined in terms of all previous Index values -- effectively as a weighted average of them. There is also the further consideration that certain selected events, called Class 1 events, are deemed to involve more intense competition than ordinary events and should be more influential in the grading process; certain other events, deemed to be contested with less seriousness, called Class 3 events, should be less influential than ordinary events; in this context ordinary events are also called Class 2 events. To this end, the Ranking Officer classifies every event into one of these three classes. At the outset, a player's Index equals the start Grade.

The postgame update algorithm for the Index is as follows:

NewIndex = OldIndex + CF * 50 * (OW-EW)

where the Class Factor CF equals CF1 = 1.2 for Class 1 events, CF = 1.0 for Class 2 events, CF = CF3 = 0.8 for Class 3 events. Class 1 games comprised 7.6% of the games under study and Class 3 games 11.1%.

Grades are updated after every game via the following grade-smoothing algorithm:

NewGrade = ASP * OldGrade + (1-ASP) * NewIndex

where ASP (= Active Smoothing Parameter) is determined as follows:

ASP = 0.9 when Index < 2000 and
ASP = 0.9 + (Index-2000)/10000 when Index >= 2000

subject to the further constraint that ASP <= 0.97. Thus ASP is in fact derived from two parameters: the Primary Smoothing Parameter PSP with value 0.9 and the Secondary Smoothing Parameter SSP with value 0.97. The latter specifies an upper bound for ASP.

In what follows, we will also encounter choices of Continuous Grading parameter values other than those just mentioned. The operational version of Continuous Grading on 14 March 2017 (the time of our data set) used the following list of parameter values:

Modulator	Sc19	CF1	CF2	PSP	SSP
50	500	1.2	0.8	0.9	0.97

We refer to this particular version of Continuous Grading as CSQ (Continuous grading of the Status Quo). The use of Sc19 = 500 serves as reminder that the system CSQ makes no distinction between bo13 and bo19 games. Our main task is to investigate whether CSQ should continue to be the official grading system and, if not, to recommend a replacement.

5. The Grade Deviation statistic (GD).

This statistic is repeatedly used as a reality check to see whether the grades delivered by a given system make sense. Consider a selected set of 10,000 game results in which the higher graded player had a win probability between 60% and 62.5%, thereby giving rise to an expectation that the higher graded player will be found to win between 6,000 and 6,250 games. Were we to count the number of games in which the higher graded player actually did emerge as the winner, we would get an impression of the extent to which the system is performing in accordance with expectations. For example, if the actual number of wins total merely 5,000 or as many as 7,000, the performance of the system would be disappointing while an observed number of 6,100 wins could be regarded approximately in accordance with expectation. However, one should not merely consider win probabilities in the range 60% to 62.5%, but also those in similar small probability intervals like 50% to 52.5%, 52.5% to 55%, and so on - subintervals that collectively cover the entire probability interval 50% to 100%. The Grade Deviation statistic is designed to provide a summary of how well a grading system performs across all chosen sub-intervals that cover the range 50% to 100%. It is expressed in terms of a single positive number (GD), such that smaller GD-values indicate better grading accuracy. We describe in Appendix 1 precisely how GD is defined and calculated (for readers who wish to know that).

Our numerous experiments with a variety of grading systems revealed that an average GD below 1.0 is attainable, where the average is taken over 53 successive disjoint batches of 3000 games each. Aside from enabling us to objectively compare one grading system with another as regards grading accuracy, the GD statistic will be seen to be also a potent diagnostic tool that can alert us to inferior or problematic performance and guide us toward improvement.

6. GD-profiles of FM and CSQ .

By **GD-profile** of a system will be meant the list of its GD-values for each batch of games. The GD-profile can be illustrated with a chart and some of its features are usefully summarized by the following related statistics:

avGD = average GD over all batches iGD = average GD

over the first 30 batches (initial GD) rGD = average

GD over the last 30 batches (**recent GD**)

GAT (= Grading Accuracy Trend) = iGD – rGD.

Here follows profiles for the two systems FM20 (FM with Modulator = 20) over the 53 batches present. We also provide the respective values for rGD, and GAT. The statistic rGD is of more interest than avGD because it reflects more recent performance. A negative value of GAT indicates that the grading accuracy over the last 30 batches was worse than over the first 30. Thus a negative GAT value quantifies deterioration over time while a positive GAT quantifies improvement of grading accuracy over time.

Batch	**FM20 GD**	**CSQ GD**	**bo19cnt**
1	1.211	1.551	0
2	1.075	1.330	0
3	0.987	0.985	0
4	0.937	1.164	0
5	0.900	1.099	0
6	1.303	1.267	0
7	1.380	1.261	6
8	1.000	1.239	10
9	0.738	1.105	195
10	1.107	1.263	93
11	1.153	1.242	198
12	0.951	1.310	73
13	1.124	1.358	152
14	1.017	1.278	128
15	0.927	1.264	174
16	0.873	1.035	65

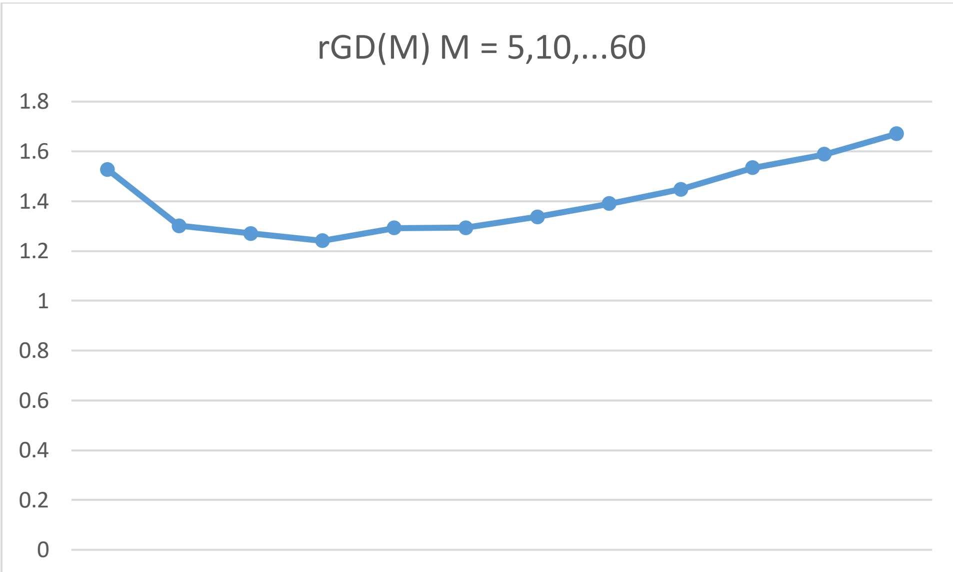
17	0.747	0.998	7
18	0.885	1.351	314
19	1.061	1.441	161
20	1.293	1.653	86
21	1.038	1.457	121
22	0.959	1.242	113
23	0.972	1.086	6
24	1.179	1.248	152
25	1.092	1.414	29
26	1.524	1.782	222
27	0.790	1.177	49
28	1.307	1.245	22
29	1.121	1.512	123
30	1.182	1.433	93
31	1.317	1.251	137
32	1.274	1.611	60
33	1.109	1.556	35
34	1.154	1.540	104
35	1.191	1.407	293
36	1.602	1.954	78
37	1.374	1.863	103
38	1.331	1.416	75
39	1.187	1.463	79
40	1.392	1.661	97
41	1.009	1.344	93
42	0.982	1.002	92
43	1.184	1.486	310
44	1.079	1.183	217
45	1.559	1.540	68
46	1.551	1.845	37
47	1.356	1.552	18
48	1.051	1.453	124
49	1.171	1.589	85
50	1.091	1.091	257
51	1.030	1.444	158
52	1.471	1.832	66
53	1.572	1.755	94
rGD	1.241	1.488	
GAT	-0.180	-0.195	

These rGD values are larger than what we would like to see. The relatively large negative GAT values indicate performance deterioration over time. We will show later that it is possible to design systems that produce a positive GAT value, at least over these 53 batches.

To get a better understanding of the role of the Modulator we list avGD , rGD and GAT for FM over 12 increasing values for the modulator:

Mdltr	**avGD**	**rGD**	**GAT**
5	1.330	1.528	-0.428
10	1.183	1.301	-0.244
15	1.162	1.270	-0.212
20	1.148	1.241	-0.180
25	1.182	1.292	-0.209
30	1.179	1.293	-0.210
35	1.216	1.337	-0.229
40	1.271	1.390	-0.219
45	1.316	1.448	-0.247

50	1.384	1.534	-0.276
55	1.458	1.588	-0.253
60	1.547	1.670	-0.245



Modulator values near 20 appears to deliver the best performance. These outcomes are consistent with our belief that the modulators below 5 are too small to bring about the auto-correction needed to keep track of improving and regressing players while those well-above 20 lead to post-game updates that will convert approximately accurate grades to inaccurate ones. Indeed, one does not even need a computer to recognize that a Modulator = 0.5 would effectively mean that player grades will remain close to the starting grades and, at the other extreme, a Modulator = 500 would instantly convert a reasonable starting grade to a useless new grade value.

Aside from appropriately addressing form fluctuation, the modulator can also perform the function of causing certain games to be more influential or less influential on the grading process than others, as is illustrated by the Class Factors in the CSQ algorithm.

Let FME denote the update algorithm obtained from that of CSQ by drastically reducing the modulator size and by removal of the grade-smoothing feature. (The Index becomes the grade, PSP and SSP disappears as parameters). The following table lists three particular grading systems obtained by assignment of the indicated parameter values, along with their performance statistics avGD, rGD and GAT.

System	Mdltr	Sc19	CF1	CF3	PSP	SSP	**avGD**	**rGD**	**GAT**
CSQ	50	500	1.2	0.8	0.9	0.97	**1.389**	**1.488**	**-0.195**
FM	18	450					**1.15**	**1.233**	**-0.166**
FME	18	450	1.2	0.8			**1.144**	**1.236**	**-0.176**

It can be seen that the indicated changes do give some improvement. However, the rGD remains unattractively large and the relatively large negative GAT still suggests conspicuous deterioration

7. The start grade problem.

Since neither the nature of the sport nor the grading system changes significantly from one batch of games to the next, we were puzzled by the conspicuous deterioration depicted by the GD-profiles of CSQ and FM20 in section 6. After much contemplation it dawned on us that what is different in every new batch is the arrival on the scene of new start grades – each one based on very little information about the player. We diagnosed this to be the main cause of the deterioration. The start grade problem is particularly severe in Golf Croquet due to its unusually high percentage of *unsettled players* i.e. players who have less than 30 games recorded in the database. Among the 5026 players in the GC database on 14 March 2017, no fewer than 3178 (63%) were unsettled. When a new player (with poor start grade) plays mostly against players with reasonably accurate grades, some automatic correction can be expected. However, if most opponents have inaccurate grades, automatic correction is much reduced if present at all – the blind cannot lead the blind. Given these unpleasant facts, a mere improvement of the update algorithm has little if any hope to overcome the mentioned deterioration of grading system performance. So we proceeded to develop a method for automatic retrospective improvement of start grades. Let us describe how it works.

We regard the first 30 games recorded for a player as the **settling games** of that player. Thus, for a player who had played at least 30 games, the **Last Settling Game** is game 30. For the 3178 unsettled players we have LastSettlingGame < 30. Our revision of a start grades is based on a formula discovered by Arpad Elo, that well known pioneer of grading systems for Chess. His Performance Grade formula (PG) for a player in terms of opponent grades in the preceding N games, is given by

PG = AOG + 500 * [log(WinRatio) - log(1-WinRatio)],

where AOG denotes the Average Opponent Grade over those N games and WinRatio = (number of wins) / (number of games played); log denotes a logarithm to base 10. We want to apply this formula to the settling games. However, the PG formula is undefined when WinRatio = 0 or WinRatio = 1 and is unstable when WinRatio is near 0 or near 1. To circumvent this obstacle, we introduce the concept AWR (**Adapted Win Ratio**) which is defined as follows

AWR = 0.1 when WinRatio < 0.1;
AWR = 0.9 when WinRatio > 0.9;
AWR = WinRatio otherwise.

In this way we arrive at the **Adapted Performance Grade formula**

(7a) APG = AOG + 500 * [log(AWR) - log(1 - AWR)].

This formula remains applicable to the settling games even when no wins or no losses are present. While APG would in general be a poor substitute for the start grade of a player, it turns out that there are hundreds of players whose start grades are so far out of line that APG provides a welcome substitute. However, it is problematic to detect the players for whom the substitution would be beneficial. We solve this detection problem in terms of the Test Difference, defined as follows:

Test Difference = APG – (Grade after the LastSettlingGame).

Players with LastSettlingGame = 30 are selected for revision when

| Test Difference | > 51,

where 51 (Revision Trigger) was determined experimentally and found to work well for each grading system under consideration. The experimental determination consists simply of monitoring the effect on the GD when the trial Revision Trigger becomes replaced by a slightly smaller or larger number. When LastSettlingGame < 30 there is less certainty about the performance level of the new player and for such players the chosen Revision Trigger is too small. By similar experimental determination we found that, at least for players with LastSettlingGame = 10 or more, the selection criterion

(7b) | Test Difference | > 51 * (2 - LastSettlingGame/30),

gives satisfactory results, so that is what we adopt. The gradual increase of Revision Trigger as LastSettlingGame drops below 30 is illustrated by the fact that the expression on the right equals 51 when LastSettlingGame = 30 and becomes 1.6 * 51 = 81.6 when LastSettlingGame = 12. All told, players having LastSettlingGame >= 10 are deemed selected for start grade revision when they satisfy condition (7b) and for such players the APG (given by formula 7a) is adopted as Start Grade. We are thus postponing the revision of players with LastSettlingGame < 10 until they have played enough games to qualify for revision. Once a player reaches LastSettlingGame = 30, the start grade of that player is no longer subject to revision.

8. Grading systems that employ automatic Revision of start grades.

The start grade revision procedure described in the preceding section gives rise to a new kind of grading system – one that makes more than one run over the game results before proceeding with the final grade updating. In the first run it determines the Last Settling Game of each player. In the second run it does the start grade revisions that are called for while doing preliminary updating of grades. About 20% of start grades become revised, some of them by several hundred grade points. In the third run it uses the revised start grades instead of the original start grades where appropriate. This may sound laborious, but in our trials we found that on an ordinary HP computer running on Windows 10 the updating for the 5026 players after 160608 games typically takes merely 7 seconds. So it should not burden the Ranking Officer unduly. On the contrary, it could eliminate much laborious manual start grade revision.

Here follows a list of four grading systems CRE0, CR1, FMR, FMRE of the new kind, along with their performance statistics. In each case the symbol for their update algorithm contains the letter 'R' as reminder that (automatic) Revision of start grades is employed and 'E' when event classification is employed.

The grading systems CRE and CR1 are obtained by modifying CSQ. First of all, the scale parameter Sc19 (see section 2) becomes reduced from 500 to 450 and the modulator is drastically reduced from 50 to 19.2; the primary smoothing parameter PSP is likewise drastically reduced from 0.9 to 0.5; the parameter SSP is effectively eliminated by setting SSP = PSP i.e. ASP no longer varies with the Index; in CR1 event classification is abolished; CRE retains event classification but with reduced sizes for the class factors, namely CF1= 1.16 instead of 1.2, CF3 = 0.76 instead of 0.8.

The system FMR is the fixed modulator system with M = 18.2.
FMRE is the fixed modulator system with M = 20.2 and in which event classification is employed with CF1 = 1.15, CF3 = 0.76.

In all cases the choice of parameter values was motivated by a desire to minimize avGD. We tabulate for convenient reference the above definitions while giving the performance statistics produced by the resulting systems.

System	M	CF1	CF3	PSP	SSP	avGD	rGD	GAT
CRE	19.2	1.16	0.76	0.5	0.5	0.989	0.982	0.02
FMR	18.2					1.002	0.992	0.03
CR1	19.2	1.15	0.76	0.5		0.998	1.006	-0.007
FMRE	20.2					1.003	1.008	-0.007

These systems do address the deterioration problem. In fact, the GAT-value of CRE and FMR are positive and the other two are close to zero.

9. Dynamic Grading.

Every sport has its own typical form fluctuation. It is consistent with section 6 to think that an increase in modulator size is called for when an increase in form fluctuation is present.

This belief underlies the idea of Dynamic Grading, namely grading in which modulator size is temporarily increased for a player whose form is rapidly improving or rapidly regressing i.e. one whose grade does not autocorrect fast enough to keep up with the rapidly changing form. Such a player will be said to be in **mobile state.** Implementation of Dynamic Grading requires two key steps: (1) detection of mobile states and (2) appropriate modulator increments. Much progress has been made as regards both these steps since the idea of Dynamic Grading was pioneered by the AC Ranking Review Committee a few years ago. Our implementation steps are much simpler while at the same time more efficient. We discovered that the APG of a player (see section 7), calculated over the preceding 30 game results, is an effective instrument for detection of mobile states. When some of the thirty opponents are over-rated and some are under-rated, a welcome cancellation of errors takes place. We define the **Mobility Index (MobIdx)** of a player by putting

MobIdx = APG – Grade.

A player is deemed to be in **mobile state** when |MobIdx| > 90. The Mobility Trigger = 90 is experimentally determined and found to be the same for all systems of interest. The modulator does not gradually increase as MobIdx increases. That would inevitably cause most players to have some increase in Modulator even when they do not really have rapidly changing form. The increase in modulator kicks in only when the condition |MobIdx| > 90 is satisfied. (This is a clear improvement over previous versions of dynamic grading).

The system DR that we now describe is, for the first 30 games of each player, nothing but the fixed modulator system FM with Modulator = 19. After game 30 and after every subsequent game the player's Mobility Index is calculated and when the player is found to be in mobile state his modulator becomes incremented by the quantity **4.4**. Thus, while ordinary players retain the usual post-game grade adjustment New Grade = Old Grade

+ 19 * (OW-EW), this algorithm **becomes replaced for players in mobile state** by the temporary algorithm

New Grade = Old Grade + (19 + 4.4) * (OW-EW).

A player may remain in mobile state for just one or two games. In that case, the incremented modulator produces negligible effect. It becomes significant when the player remains in mobile state for several games in succession. Practically all active players experience significant periods in mobile state even though these periods may be few and far between.

The system DRE is the variant of DR obtained by introducing event classification, much as FMRE above was derived from FMR. The basic modulator that it departs from is 18.8.
The system DREA is another variant of DR obtained via introduction of event classification. However, its Class 1 events differ from traditional ones appearing in DRE (prestigious ones, so deemed at the discretion of the Ranking Officer). Class 1 events in DREA are determined via an algorithm. Namely, the event needs to be populated by at least 16 players and the average of the top 16 entered grades need to exceed the prescribed minimum **C1 Trigger = C1T** = 2195. This restriction does not diminish the number of events selected. On the contrary, it greatly increases them, as follows:

349	DREA Class 1 events
83	DRE Class 1 events
34	common to both

The precise definitions for the following three systems are completed by the specified parameter values, chosen so as to produce the smallest avGD.

System	Mdltr	CF1	CF3	avGD	rGD	GAT
DR	18.9			0.989	**0.968**	**0.050**
DRE	18.8	1.16	0.76	0.968	**0.967**	**0.018**
DREA	19	1.12	0.72	0.952	**0.939**	**0.043**

The DREA Class 1 selection algorithm is implemented as follows. As with DR, the first run determines the Last Review Games, the second run does the start grade revisions, the third run (based on the revised start grades and using the Class 3 events already in the database) calculates the DR-like grades used for selection of the DREA Class 1 events. The fourth run uses the revised start grades and the selected DREA Class1 events in addition to the known C3 events to produce the final updated DREA grades.

The designs of these dynamic grading systems arise from insights gained from the modulator studies reported in section 6. Ultimately they do not rest on theoretical considerations but on experiments that found a combination of parameters that produced an optimally appearing avGD. They produce excellent rGD and they seem to address the deterioration problem more vigorously than those of section 8, as can be seen from their substantially positive GAT-values – obtained despite good iGD values.

10 Grade-smoothing update algorithms.

The systems CSQ, CRE0 and CR1 (introduced in sections 4 and 8) use a Grade and Index and the update algorithm

New Grade = ASP * Old Grade + (1-ASP) * (New Index).

It is grade-smoothing in that the Grade progresses more smoothly than the Index from which it is derived.

It is readily seen via a little algebra that

New Grade > Old Grade when New Index > Old Grade (even with a lost game),
New Grade < Old Grade when New Index < Old Grade (even with a won game).

Thus a grade may increase after a lost game or decrease after a won game, thus producing a **non-intuitive grade adjustment.** Of the 2 * 160608 grade adjustments produced by CSQ, no fewer than 97324 (or 30.3%) were of this non-intuitive kind. Undesirable influence on players may result: when a player is in a situation where his grade will decrease after his next game regardless of whether he wins or loses, he may be disinclined to play any game at all; more so when an important seeding or selection decision is pending in which his grade may be influential.

The grade-smoothing feature of CSQ was presumably introduced because the relatively large Index value of 50 caused unacceptable volatility. We define **volatility** to be the average absolute grade adjustment per player per event. In terms of this measure the volatility of a fixed modulator system is approximately equal to the size of its modulator: a modulator 50 produces volatility of approximately 50 while a modulator 20 produces a volatility of approximately 20, which is comparable to the volatility 17.5 of CSQ. Since the candidate systems under consideration typically have a modulator near 20, volatility is no longer the problem that it was once thought to be.

Does grade-smoothing improve grading accuracy? It will be seen to depend on the setting. CSQ can be regarded as FME + grade-smoothing. In the context in which CSQ operates (large modulators and poor start grades) the avGD and rGD produced in experiments suggest that grade-smoothing does improve grading accuracy. The system CR1 can similarly be regarded as FMR + grade-smoothing and likewise CRE = FMRE + grade-smoothing. Let us recall their performance statistics while adding two more systems CR2 and CR3:

System	Mdltr	CF1	CF3	PSP	avGD	rGD	GAT
CRE	19.2	1.16	0.76	0.5	0.989	0.982	0.020
CR1	19.2			0.5	0.998	1.006	-0.007
FMR	18.2	1.15	0.74		1.000	0.988	0.031
FMRE	20.2				1.000	1.005	-0.005
CR2	19.2			0.7	1.003	1.018	-0.029 -
CR3	19.2			0.9	1.065	1.075	0.012

These results again suggest that grade-smoothing does slightly improve grading accuracy, provided that the smoothing parameter PSP becomes drastically reduced from the traditional value 0.9 to 0.5; otherwise it gives worse grading accuracy.

The question arises of whether the grading accuracy of DR can be improved by grade-smoothing: when DR becomes cast in the role of Index and then supplemented by a Grade based on various values of the smoothing parameter. The following results were obtained for the algorithm CDR so created:

PSP	Mdltr	avGD	rGD	GAT
0	18.9	0.989	0.968	0.05
0.1	18.9	0.991	0.96	0.069
0.2	18.9	1.004	0.983	0.049
0.3	18.9	1.01	0.976	0.065
0.4	18.9	1.013	0.978	0.061
0.5	18.9	1.029	0.998	0.062
0.6	18.9	1.035	1.005	0.052
0.7	18.9	1.029	1.015	0.03
0.8	18.9	1.021	1.019	0.005
0.9	18.9	1.042	1.063	-0.019

The performance of the algorithm CDR turns out to be best when PSP = 0 (i.e. when CDR reduces to DR) and gets steadily worse when PSP is made larger. Similar results are obtained when the basic modulator becomes changed from 18.9 to other values. Also when DRE or DREA are substituted for DR, although the progression for varying PSP is not as regular in these cases. All told, the results obtained do not encourage the use of grade-smoothing as instrument for improvement of grading accuracy beyond that attained by DR, DRE or DREA.

11. Performance statistics over more recent data.

We now present performance statistics over more recent game results: namely, games up to 30 September 2017. This includes 59 batches of 3000 games. The previous performance statistics were obtained after parameter choices that attempted to find the smallest avGD (average GD over the 53 batches). The new performance statistics are of interest because they include at least 6 batches that had no influence on the parameter choices. So we are using the first 53 batches for "training" and then the last 30 of the 59 batches for "testing", which includes at least 6 new batches. From some points of view it would seem better to use fewer batches for training so as to have more new batches available for testing, but that creates another problem. The bo19 games (not uniformly distributed over the 53 games, as shown in section 6) and some parameters (like CF1, CF3) involve a relatively small number of games, thus a larger training sample seemed more appropriate as a basis for good parameter choices. Better testing opportunities will naturally come in future as new game results accumulate. The computer can effortlessly provide ongoing performance statistics.

The following table presents the profiles of DRE over the original 53 batches and then over the 59 batches respectively.

Batch	GD53	Batch	GD59
1	1.095	1	1.093
2	1.026	2	1.07
3	1.052	3	1.056
4	0.96	4	0.946
5	0.914	5	0.906
6	1.013	6	1.341
7	1.025	7	1.015
8	1.062	8	0.979
9	0.793	9	0.733
10	1.027	10	0.966
11	0.926	11	0.881
12	0.615	12	0.902
13	1.003	13	0.942
14	1.179	14	1.047
15	1.039	15	0.958
16	0.816	16	0.939
17	1.049	17	1.156
18	0.982	18	0.889
19	0.893	19	1.112
20	1.231	20	1.085
21	0.83	21	0.858
22	0.892	22	0.928
23	0.848	23	1.019
24	0.985	24	0.937
25	1.001	25	1.208
26	1.408	26	1.269
27	0.954	27	0.943
28	0.943	28	0.95
29	0.934	29	0.938
30	1.056	30	1.079
31	0.85	31	0.982
32	0.737	32	0.817
33	0.939	33	1.016
34	1.061	34	1.038
35	1.191	35	1.236
36	1.376	36	1.195
37	0.744	37	0.886
38	1.207	38	1.406
39	0.764	39	0.893
40	1.06	40	1.062
41	0.797	41	0.68
42	1.135	42	1.215
43	0.865	43	0.843
44	0.887	44	1.145
45	0.757	45	0.68
46	1.136	46	1.21
47	0.851	47	0.836
48	0.801	48	0.88
49	0.821	49	0.704
50	0.957	50	1.03
51	0.683	51	0.833
52	1.12	52	1.078
53	0.991	53	0.674
		54	1.11

		55	0.917
		56	1.2
		57	1.021
		58	1.07
		59	1.276
rGD53	GAT53	rGD59	GAT59
0.967	0.018	1.000	0.005

The rGD53 and GAT53 entries give the rGD and GAT values as calculated from the GD53 column of the original 53 batches while the rGD59 and GAT59 entries are calculated from the GD59 column. It is worth noting that the GD53 and the GD59 entries over the first 53 batches of the GD59 column are generally slightly different. The differences arise in more than one way. There will normally be a change in the game results as late arrivals become inserted into the first 53 * 3000 games. Differences of this kind arise mostly in batch 53. Another kind of difference, due to start grades, may arise in any batch from 1 to 53. A player may play 9 or fewer games in batch 1 and then nothing until playing a few games in batch 58 (say). So DRE would not have revised his start grade until batch 58. But then, in the final DRE grading run, the new start grade would influence the results of all batches, from 1 to 59. Given the large number of unsettled players it is no surprise that this kind of difference could arise repeatedly.

The last 30 GD values, together with the statistics rGD and GAT (see the high lighted entries in the above table) provides a virtual ongoing audit of the system performance. Continued good performance cannot be guaranteed. It is clear from the above tabulation of rGD59 and GAT59 that in just 6 months and with 6 new batches some deterioration of performance became visible in all systems. What will the performance look like after two more years? Or after 5 more years? There are a number of influences over which nobody has control. The quality of new start grades is one of them. The automatic start grade revision that we introduced does not address all potential start grade problems. For example, if a local pool of players should develop who mainly play each other, then their grades may be accurate relative to each other while all of them are 200 points too high relative to the general population. Such a problem can go undetected for a few years and then suddenly come to light. It cannot be addressed by changing parameters; it requires a change in start grades additional to what our method is offering.

The table to follow summarizes the performances of the mentioned systems. The list is sorted on column rGD59.

System	**rGD53**	**GAT53**	**rGD59**	**GAT59**
DRE	0.967	0.031	**1.000**	0.005
DREA	0.939	0.043	**1.011**	-0.004
DR	0.968	0.050	**1.015**	0.008
CR1	1.006	-0.007	**1.024**	-0.023
FMRE	1.008	-0.007	**1.025**	-0.010
FMR	0.992	0.03	**1.038**	-0.007
CRE	1.006	-0.007	**1.059**	-0.067
CSQ	1.488	-0.195	**1.555**	-0.278

Since a good fit on the 53 batch data is unlikely to be an equally good fit on the new data which had no influence on the parameter choices, it is not surprising to see a worsening of all rGD values. DRE and DR are the only systems to retain a positive GAT, albeit by a small margin. The systems in the top group are joined by FMR and FMRE in the middle group to have a |GAT| that does not exceed 0.01.

DREA has the dubious distinction of giving the largest difference rGD59 – rGD53 = 0.072 among all the listed systems; it is more than double the difference 0.033 produced by DRE. Was the rGD53 = 0.939 produced by DREA an outlier?

12. Ranking Comparisons.

Let us compare rankings on 30 September 2017 for players who had played at least 20 games in the preceding 12-month period. For this purpose we introduce the metric SAARD (Symmetric Average Absolute Rank Difference) which the croquet public may understand better than the correlation coefficients used in statistics. Towards an explanation of how SAARD is calculated, consider the top 12 ranked players for DRE (the system with the best rGD59). For each of them we find

(DRE,CSQ) Rank Difference = DRE-rank – CSQ-rank.

For example, for R Bamford this rank difference is 0 while for S Mostafa it is 12 – 13 = -1. The absolute rank difference is |-1| = 1. By adding, we find the sum of absolute rank differences for the top 12 on the DRE rank list. We similarly compute the sum of absolute rank differences for the top 12 on the CSQ list (for which we use the fact that G Fletcher, ranked 12 on the CSQ list and 14 on the DRE list, and so contributes the absolute rank difference |12 – 14| = 2. By adding together the absolute rank differences of the top 12 on the DRE list and the top 12 on the CSQ list and dividing by 24 (= 2 * 12) we obtain the number

SAARD(DRE,CSQ) (= Symmetric Average Rank Difference between DRE and CSQ).

Note that SAARD(DRE,CSQ) = SAARD(CSQ,DRE) even though the same 12 players do not appear in the two Top12 lists in question. While the above was done for the Top 12, a similar calculation can be done for the Top N, where N is any positive integer up to the total of ranked players. On this occasion that total came to 731. The table to follow reports SAARD values for selected pairs of systems.

		Top10	**Top100**	**Top500**	**Top731**
Sys1	**Sys2**	**SAARD**	**SAARD**	**SAARD**	**SAARD**
CSQ	DRE	0.8	12.3	22.9	22.7
CSQ	DR	1	12.4	22.9	22.7
CSQ	DREA	1	12.4	23.1	22.8
CSQ	FMRE	1.2	12.8	24.4	24.3
CSQ	CR1	1.2	13	24.1	23.8
FMRE	DR	0.4	2	4.1	4.1
FMRE	DREA	0.4	2	4.1	4.2
FMRE	DRE	0.6	2	3.5	3.5
CR1	DR	0.4	3.1	6	5.7
CR1	DREA	0.2	3	6.1	5.9
CR1	DRE	0.4	3.1	6	5.7
DRE	DREA	0.2	0.9	2.1	1.9
DRE	DR	0.2	0.8	1.7	1.9
DR	DREA	0	0.9	2.3	2.5

The Top100 SAARD value is of particular interest for World Championships and other prestigious events. It is reassuring to see that rGD differences are remarkably consistent with SAARD differences: the large rGD difference between CSQ and those that employ dynamic grading (1.555 compared to values near 1.0) is reflected in the fact that

SAARD Top100 > 12 in case of CSQ while

SAARD Top100 < 1 in case of DR, DRE, DREA

The systems FMRE and CR1 are clearly different as regards SAARD Top100: 2 and above 3 for the former compared to below 1 for the dynamic group. The ranking of the latter three systems are virtually the same from top to bottom as regards Top100 comparison and with no remarkable difference even in the Top500.

The displayed ranking list for DRE in Appendix 2 shows that F Webby had, at the time of the list, a Mobility Index of 102, which indicates that he was in mobile state at the time. Furthermore, the column MobStrk with entry 19 indicates that he had been in mobile state for 19 games in a row. The only other Top 12 player shown there to be in mobile state is D Dixon, who was just in the second game of his streak. Active players mostly encounter a mobile streak (up or down) sooner or later. It is only when it lasts for several games that it makes a noticeable difference.

Appendix 1

THE GRADE DEVIATION STATISTIC

The AC Ranking Review Committee called attention to the long known Chi-squared statistic (see [ITDG] http://www.oxfordcroquet.com/tech/nel-dg/index.asp) as an effective method for comparing the grade difference accuracy of various grading systems. They also introduced an equivalent version of it, called Grade Deviation (GD), with values in a more convenient interval.

How GD is calculated.

Except where otherwise stated, the GD reported in this document will be calculated over batches of 3000 games. The Probability Interval with endpoints 0.5 and 1.0 is subdivided into 20 abutting subintervals Int_k (k=1,2,…20), each of diameter 0.025, as follows:

Int_1 going from $L_1 = 0.500$ to $R_1 = 0.525$
Int_2 going from $L_2 = 0.525$ to $R_2 = 0.550$
etc.

The grading system being evaluated automatically decides, for every game, to which one of these subintervals Int_k the win probability of the higher graded player belongs. Thus the set of games automatically becomes subdivided into 20 pairwise disjoint subsets Bin_k (k = 1,2,…20). These subsets are called *bins*. For each bin it can be counted how many games are classified so as to belong to it. So we get the list of numbers GIB_k (k=1,2,…20) (Games In Bin).

Let $OWhg_k$ denote the number of games in Bin_k in which the higher graded player emerged as the winner and let $EWhg_k$ be the summed win probabilities of the higher graded players. If the subinterval Int_k happens to be the subinterval with left endpoint 0.6, then it can be expected that $EWhg_k$ should be about 60% of GIB_k. Since nothing is ever perfect, it will often hold slightly more or slightly less than that. The difference

$OWhg_k – EWhg_k$ = (Observed wins – Expected wins)

in Bin_k, lies at the core of the GD statistic. *The difference $OWhg_k – EWhg_k$ represents the discrepancy between the observed number and the expected number of games in Bin_k.* It is already, just as it stands, a crude evaluation of grading accuracy. It needs to be refined because results for one probability interval (e.g. near 0.6) may not be representative enough. It also needs to take into account the fact that the different bins hold different numbers of games. So some statistical processing is involved before the 20 crude evaluations $OWhg_k – EWhg_k$ can be summarized in one number GD that usefully estimates the grading accuracy of the system over the entire probability range.

For each test game g we have an "atomic" random variable OWhg whose value OWhg(g) at game g is 1 or 0 according to whether the higher graded player did or did not win the game. There is a second random variable EWhg in sight, whose value EWhg(g) is the win probability of the higher graded player at game g. This value can be estimated by calculating the win probability via the grades of the players (see formula 1.1) . These atomic random variables arising from different games g are deemed to be independent. By summing them we arrive at random variables

$OWhg_k$ = Sum{OWhg(g) | g in Bin_k } and

$EWhg_k$ = Sum{EWhg(g) | g in Bin_k }

such that the latter is the expected value of the former in the usual technical sense of random variable theory. The variance of OWhg(g) is found to be EWhg(g) * (1-EWhg(g)) and, in view of the independence, the variance V_k of $OWhg_k$ can be shown (after some nifty algebraic manipulation) to be given by the sum of the variances:

V_k = Sum{ EWhg(g) * (1-EWhg(g)) | g in Bin_k }

This leads naturally to the standardization Z_k of OWhg_k, given by the expression

$Z_k = (\text{OWhg}_k – \text{EWhg}_k)/\text{sqrt}(V_k)$.

The process of standardization transforms an arbitrary random variable to one with Expected Value = 0 and Standard Deviation = 1 (The quantity sqrt(V_k) is the Standard Deviation of OWhg_k.) Standardized random variables can be compared with each other regardless of the sizes of their original underlying sample spaces. Finally, taking the root-mean-square, we get the *Grade Deviation statistic*

$\text{GD} = \text{sqrt}((Z_1^2 + Z_2^2 + \ldots + Z_{20}^2)/20)$.

Example (from a specific batch of a specific grading system).

Bin	BLB	BUB	GIB	OW	EW	OW-EW	V	Z
1	0.5	0.525	223	121	114.33	6.669	55.7	0.894
2	0.525	0.55	212	107	114.05	-7.052	52.68	-0.972
3	0.55	0.575	216	119	121.53	-2.527	53.14	-0.347
4	0.575	0.6	225	126	132.07	-6.07	54.54	-0.822
5	0.6	0.625	204	124	124.98	-0.977	48.4	-0.14
6	0.625	0.65	182	105	115.94	-10.94	42.07	-1.687
7	0.65	0.675	160	105	105.83	-0.832	35.82	-0.139
8	0.675	0.7	158	117	108.64	8.36	33.93	1.435
9	0.7	0.725	174	129	124.04	4.962	35.61	0.832
10	0.725	0.75	176	125	129.73	-4.734	34.09	-0.811
11	0.75	0.775	139	98	105.87	-7.875	25.22	-1.568
12	0.775	0.8	170	129	133.83	-4.828	28.47	-0.905
13	0.8	0.825	147	115	119.33	-4.327	22.46	-0.913
14	0.825	0.85	116	93	96.91	-3.914	15.94	-0.98
15	0.85	0.875	132	117	113.9	3.102	15.61	0.785
16	0.875	0.9	133	122	118.04	3.958	13.27	1.087
17	0.9	0.925	72	66	65.54	0.46	5.88	0.19
18	0.925	0.95	85	82	79.53	2.473	5.12	1.093
19	0.95	0.975	56	55	53.92	1.078	2	0.763
20	0.975	1	20	20	19.62	0.378	0.37	0.621

The statistic GD is closely related to the *Chi-squared statistic,* given by

$\text{ChiSq} = Z_1^2 + Z_2^2 + \ldots + Z_{20}^2$.

The latter is widely used in statistics. It has a larger order of magnitude than the Z-values from which it is derived. GD, having the same order of magnitude as the Z-values, is more convenient for our purposes. The obvious mapping that carries ChiSq to GD, as well as its inverse mapping, preserves order and is continuous. In an idealized situation every Z_k would be 0 (being a standardization). So GD can be interpreted as a measure of how far the grading system falls short of being ideal.

The definition of GD made here involves choices that arise from practical considerations. The relatively small Batchsize = 3000 allows many batches in the available set of game results and thus allows useful scrutiny of how the grading system performance varies over time. The choice of Batchsize influences the choice of Bins = 20: too many bins would result in GIB entries that are too small. These choices are not critical: a slight increase or decrease in the number of bins or in the Batchsize does not significantly influence the resulting GD.

Appendix 2

A DRE RANKING LIST

Here follows a DRE ranking at 30 September 2017 for all players who had played at least 20 games in the preceding 12 month period. The column on the left gives the CSQ rank position, for convenient comparison. Anybody who thinks all grading systems are basically the same should look through these two columns from top to bottom. Even the top 100 will bring to light conspicuous differences. It lists also Grade, Career Games Played, Games In Ranking Period, Wins, Mobility Index, Mobility Streak.

CSQrank	DRErank		Grade	CGP	GIRP	Wins	MobIndex	MobStrk
1	1	R Bamford	2718	832	83	68	-73	0
2	2	A Nasr	2687	671	102	81	-76	0
3	3	H Erian	2652	522	91	70	-23	0
5	4	A Alebiary	2634	398	75	54	-6	0
4	5	F Webby	2633	260	142	112	104	19
7	6	M Nasr	2591	725	83	59	-69	0
9	7	M Karem	2585	504	71	49	54	0
6	8	J Moberly	2582	468	125	101	4	0
10	9	D Dixon	2579	660	66	50	146	2
8	10	M Nezar	2553	480	56	39	-27	0
11	11	S Sabra	2543	272	48	32	-4	0
13	12	S Mostafa	2516	424	55	45	-26	0
14	13	J Clarke	2498	467	29	19	-25	0
12	14	G Fletcher	2479	54	30	24	90	0
19	15	A El Mahdi	2466	630	88	57	-105	1
29	16	A Yasser	2459	315	20	15	-34	0
20	17	W Gee	2456	664	22	19	57	0
16	18	J Freeth	2452	364	154	122	-43	0
27	19	A Hani	2446	90	25	18	79	0
24	20	A Baher	2443	371	26	16	-96	2
22	21	S Mulliner	2435	1464	161	114	-31	0
18	22	M Walid	2435	232	77	48	-36	0
28	23	F Farouk	2433	263	36	21	-49	0
21	24	I Burridge	2433	400	162	115	18	0
35	25	A Hilal	2432	166	49	30	7	0
26	26	M Taha	2432	221	37	22	-71	0
23	27	R Rowe	2424	716	92	65	34	0
15	28	P Landrebe	2424	444	47	31	-19	0
37	29	P Salib	2421	444	91	58	26	0
52	30	A Hisham	2415	71	22	14	-141	4
36	31	J Powe	2415	157	69	59	53	0
25	32	E Wilson	2415	52	52	37	110	8
17	33	E Fordyce	2408	213	72	53	43	0
31	34	G Coulter	2407	344	97	66	-16	0
56	35	A El Amari	2390	83	25	15	47	0
44	36	M Mostafa	2389	484	73	47	-45	0
160	37	M Salah	2387	23	23	13	0	0
51	38	H Mahmoud	2386	288	35	25	30	0
40	39	M Nabil	2382	290	96	69	-89	0
62	40	S Aziz	2379	305	25	16	-48	0
30	41	S Abdelwahab	2379	524	43	27	43	0
38	42	S Hassan	2375	536	45	24	-95	1
41	43	T Stephens	2371	582	63	52	13	0
47	44	K Ghamry	2368	167	34	15	37	0
63	45	O El Hawash	2366	323	33	20	50	0
64	46	M El Derdiri	2361	342	61	41	-26	0
50	47	H Shaker	2359	61	20	11	68	0
54	48	K Kamal	2359	195	57	31	-72	0

42	49	A Abdelshafei	2349	92	34	21	66	0
65	50	Y Esmat	2344	562	50	25	29	0
39	51	H Mcintosh	2343	394	91	56	-71	0
46	52	N Mounfield	2340	150	28	19	-15	0
55	53	A Nagha	2339	161	42	25	-94	1
32	54	J Alvarez-Sala	2336	191	62	54	135	30
60	55	H Mclaren	2336	439	118	70	159	11
43	56	T Savage	2336	497	106	72	-103	1
49	57	P Fitzgerald	2333	225	29	21	-39	0
78	58	H Ouda	2332	225	45	22	-1	0
34	59	P Beaudry	2331	1086	82	63	-154	3
45	60	P Drew	2327	453	23	13	16	0
81	61	W Wahban	2327	233	58	27	-10	0
71	62	W Shahine	2325	203	22	10	-4	0
93	63	Y Fathy	2325	203	53	28	-16	0
84	64	T Mamdouh	2323	320	55	27	-48	0
59	65	O Fahmy	2323	241	66	36	-39	0
77	66	M Ali Mohsen	2321	422	36	23	70	0
73	67	A Hassan	2321	309	81	43	-33	0
69	68	C Mcwhirter	2317	1156	159	114	-83	0
48	69	J Christie	2316	841	102	65	-86	0
70	70	A Amin	2315	135	50	26	-7	0
61	71	M Kamal	2312	305	53	31	-45	0
98	72	M Rashad	2312	102	68	42	-26	0
57	73	D Walters	2311	331	23	10	-164	20
33	74	J Riva	2309	100	41	32	-79	0
75	75	S Khalil	2309	238	27	18	4	0
88	76	H Rashad	2302	214	73	42	44	0
102	77	G Karam	2293	136	33	23	61	0
94	78	H El-Bibani	2286	202	49	27	-84	0
83	79	K Tharwat	2284	213	50	27	-34	0
76	80	L Hughes	2280	624	75	53	88	0
72	81	W Dickson	2271	681	24	13	94	1
99	82	G Scurfield	2270	369	107	71	18	0
109	83	H Abousbaa	2269	527	67	30	-25	0
138	84	A El Safti	2268	89	23	14	82	0
122	85	A El Khouli	2267	275	40	19	-62	0
66	86	B Bullen	2265	190	47	35	52	0
95	87	H Yassin	2263	233	39	12	-63	0
79	88	J Goodbun	2262	570	34	25	6	0
91	89	I Sexton	2262	231	33	28	-57	0
92	90	K Beard	2261	901	116	77	-17	0
174	91	N Hosam	2254	30	24	14	-9	0
111	92	M Eissa	2253	473	63	27	-137	12
76	93	L Hughes	2253	449	123	65	93	1
104	94	I Adel	2252	149	27	15	-16	0
90	95	D Openshaw	2250	417	31	17	-23	0
67	96	F Brockway	2248	404	33	25	72	0
68	97	T King	2248	1647	157	99	95	1
127	98	S Abousbaa	2247	321	53	22	-119	3
101	99	N Mchardy	2246	102	23	16	8	0
85	100	N El Menoufi	2243	270	85	44	-29	0
106	101	A Verge	2242	322	22	11	-27	0
96	102	M Khoudeir	2241	392	58	29	-28	0
74	103	D Bulloch	2241	623	92	50	14	0
53	104	R Romero	2236	176	78	63	-33	0
112	105	J Hobbs	2235	75	53	29	-4	0

129	106	S Mamdouh	2234	210	33	19	-5	0
107	107	M Badr	2233	115	28	7	-21	0
105	108	N Archer	2231	456	87	51	1	0
114	109	M Clarke	2231	803	130	90	98	3
118	110	W Iskander	2231	66	21	10	-14	0
133	111	S El Tarahouni	2230	137	21	10	-3	0
89	112	S Mullaaliu	2230	274	25	18	-111	4
110	113	M French	2228	721	128	81	31	0
144	114	H El Atfi	2227	124	26	12	-87	0
115	115	A Mayne	2227	168	30	24	-92	1
103	116	H Mostafa	2227	326	49	26	-61	0
87	117	S Williams	2227	235	26	13	-133	2
58	118	A Alvarez-Sala	2225	236	67	53	17	0
125	119	N Harbi	2222	138	23	13	-28	0
126	120	N Ahmed	2216	400	122	65	-75	0
108	121	N Cheyne	2216	730	43	23	14	0
100	122	M Town	2215	272	25	17	17	0
120	123	M Crashley	2213	557	116	59	9	0
119	124	T Hopkins	2208	269	87	49	-26	0
157	125	I El Faransawi	2208	409	37	20	-11	0
128	126	M Daley	2206	214	70	39	30	0
80	127	A Coulter	2202	207	111	72	135	4
123	128	L Tibble	2202	1004	214	137	-72	0
131	129	B Cumming	2201	140	26	18	-38	0
173	130	W Hussein	2200	48	28	12	31	0
149	131	H Zaghloul	2200	184	34	17	-17	0
161	132	S Riley	2199	41	23	20	3	0
155	133	A Mostafa	2198	349	26	10	-115	9
113	134	A Sharpe	2198	273	48	29	-99	2
153	135	S Yousif	2196	72	44	25	-57	0
121	136	E Newell	2192	849	71	35	-110	2
146	137	M Hegazi	2191	390	28	16	11	0
130	138	D Mcloughlin	2187	463	106	70	-73	0
141	139	D Alaam	2187	92	35	16	-30	0
158	140	D Roberts	2183	332	51	38	-60	0
134	141	L Simpson	2183	436	110	67	-10	0
142	142	R Khourshed	2182	120	30	15	68	0
137	143	B Mchardy	2180	632	213	128	24	0
154	144	C Sheen	2179	1606	76	51	83	0
163	145	D Dray	2178	531	28	18	10	0
147	146	D Hanbidge	2176	287	194	114	60	0
151	147	S Saad	2175	233	24	15	1	0
143	148	G Jamieson	2174	539	121	71	-43	0
148	149	R Mcbride	2172	686	225	155	-19	0
116	150	K Murphy	2171	136	21	7	-119	8
124	151	R Bilton	2169	322	200	116	-57	0
140	152	D Crawford	2169	406	49	36	-92	6
139	153	A El Said	2164	207	59	27	29	0
170	154	L Palmer	2164	119	33	22	-33	0
82	155	B Iglesias	2163	252	92	71	-109	1
136	156	M Adel	2163	108	41	21	-45	0
152	157	C Roberts	2162	738	139	81	9	0
190	158	S Oukasha	2160	330	27	11	-41	0
145	159	C Britt	2157	248	119	77	12	0
117	160	M Stephens	2153	74	24	16	90	0
200	161	M El Barkouki	2150	127	37	21	-53	0
194	162	M Abdelrazek	2148	288	31	15	-22	0

97	163	N Zelcans	2148	488	72	60	-111	2
175	164	T El Khoudary	2146	148	39	17	64	0
135	165	R Brooks	2143	1280	183	94	33	0
162	166	B Hess	2137	544	26	20	-39	0
178	167	S Carter	2137	589	76	48	10	0
225	168	K Adel	2137	29	20	11	0	0
132	169	A El Nahas	2135	91	61	32	-61	0
166	170	R Michalsen	2135	527	107	58	117	1
156	171	M Griffith	2133	222	87	46	-3	0
164	172	M Abu El Soud	2132	142	30	17	74	0
188	173	H Ali	2127	155	28	13	30	0
159	174	D Frost	2126	192	47	31	174	8
193	175	E Coverdale	2125	42	21	15	-76	0
280	176	S Hathrell	2123	20	20	16	0	0
168	177	D Strover	2121	908	43	26	15	0
177	178	D Wise	2120	987	127	73	-14	0
220	179	M Iskander	2115	183	26	14	18	0
189	180	D Saad El Din	2113	97	29	17	28	0
172	181	S Custance-Baker	2110	165	122	88	-97	1
150	182	P Swanson	2109	255	53	34	-54	0
180	183	P Freer	2109	1383	193	106	-9	0
171	184	N Morrow	2108	1495	40	25	-63	0
214	185	O El Said	2107	138	57	26	-81	0
206	186	J Noble	2106	178	118	66	15	0
186	187	N Mamdouh	2106	70	34	16	42	0
192	188	D Beck	2105	1118	59	37	-51	0
185	189	I Norris	2104	158	33	18	29	0
196	190	J Grindrod	2103	115	102	64	27	0
212	191	D Ali Maher	2102	81	47	21	-11	0
187	192	J Elebo	2102	337	45	24	-152	13
213	193	R Barnacle	2102	211	28	19	-60	0
197	194	J Van Der Touw	2101	1025	132	73	-97	17
176	195	P Dowd	2101	226	77	44	-38	0
165	196	A Sands	2099	279	107	67	-37	0
182	197	G Whiteway	2098	504	24	17	-115	4
199	198	A Mourad	2098	278	44	22	-48	0
195	199	H Hanafi	2096	218	51	22	-36	0
286	200	K Cooper	2094	92	27	21	-110	30
198	201	E Elebo	2091	200	42	22	-70	0
207	202	A Quinn	2089	625	20	4	-89	0
226	203	M Abdelrehim	2089	128	22	9	-101	2
201	204	K Reynolds	2088	757	23	12	-56	0
260	205	J Wembridge	2088	687	117	77	-95	32
183	206	E Dymock	2086	360	23	17	4	0
179	207	E Farrow	2085	278	79	46	38	0
229	208	D Bell	2081	439	70	39	-67	0
167	209	J Richardson	2080	192	72	36	-49	0
230	210	J Murfett	2074	39	21	18	60	0
203	211	P Nicholson	2072	734	138	78	-44	0
204	212	G Hopkins	2070	356	137	82	-8	0
211	213	W Usbeck	2070	499	24	15	-235	31
254	214	S Lightbody	2069	227	30	11	-49	0
258	215	M Abdelhalim	2069	221	23	7	-106	1
191	216	T Bak	2069	337	105	65	1	0
216	217	J Levick	2068	1235	152	82	17	0
215	218	F Hassan	2068	110	23	13	-1	0
184	219	D Tutt	2066	141	30	22	74	0

221	220	M Ali Maher	2061	113	38	19	0	0
169	221	R Stafeckis	2061	443	76	46	106	1
208	222	U Soderberg	2058	280	32	18	-9	0
228	223	R Prosser	2058	111	27	19	68	0
202	224	P Balchin	2056	502	103	50	46	0
210	225	B Rowe	2056	72	21	14	-29	0
241	226	A Cowing	2054	168	29	15	-101	6
217	227	M Albert	2053	119	33	26	31	0
218	228	D Widdison	2053	420	156	96	5	0
234	229	M Hills	2052	142	62	34	-43	0
240	230	D Hector	2049	149	22	15	-7	0
276	231	M Ayman	2049	123	23	5	-43	0
219	232	G Giles	2046	228	151	87	-31	0
181	233	G Alvarez-Sala	2046	184	24	20	39	0
238	234	P Errington	2046	96	22	14	-53	0
38	235	S Hassan	2044	88	24	12	96	2
232	236	A Moldin	2043	289	24	14	-47	0
352	237	W Hoffman	2042	21	21	16	0	0
223	238	J Arney	2042	626	199	107	-11	0
231	239	W Heaphy	2041	408	33	13	-4	0
235	240	D Goacher	2040	44	22	14	31	0
224	241	D Chapman	2040	118	34	21	68	0
237	242	R Rillie	2040	320	133	73	63	0
248	243	R Tillcock	2039	222	28	16	-68	0
233	244	G Azmi	2039	62	23	10	102	2
265	245	N Eatough	2038	314	20	13	-167	13
236	246	S Zeidan	2038	151	28	11	29	0
244	247	N Hind	2037	82	23	16	-44	0
270	248	E Zadow	2037	36	36	24	-52	0
292	249	P Johnson	2034	414	26	15	-98	1
222	250	G Good	2029	360	78	49	3	0
209	251	J Steins	2027	471	97	62	-112	23
287	252	S Peters	2025	156	21	12	-13	0
288	253	D Barrett	2024	148	24	15	-42	0
246	254	I Petersen	2019	186	55	30	-30	0
245	255	P Emmett	2016	176	20	10	-38	0
261	256	I Cobbold	2013	185	40	21	-18	0
290	257	P Montague	2008	314	108	59	-85	0
281	258	D Reyland	2007	897	41	25	-6	0
257	259	T Black	2005	347	100	55	-72	0
338	260	I Morrison	2004	101	23	13	-113	18
296	261	I Bassett	2004	43	43	25	86	0
243	262	J Peck	2003	366	47	30	-31	0
259	263	P El Waei	2003	47	21	13	58	0
251	264	P Mccreadie	2003	71	29	21	164	20
291	265	A Forbes	2001	255	35	21	-3	0
205	266	S Romero	2000	250	42	30	66	0
273	267	B Haydon	1998	479	138	64	99	1
274	268	E Miller	1998	700	89	55	-23	0
277	269	G Hull	1998	271	117	63	-15	0
239	270	R Goldring	1997	484	183	82	66	0
282	271	D Hopkins	1996	1245	46	24	-30	0
289	272	R Sutton	1994	309	81	49	-23	0
275	273	J Pringle	1992	692	80	56	80	0
293	274	G Wallin	1992	287	24	10	1	0
250	275	S Thornton	1991	599	90	48	11	0
249	276	D Woods	1990	305	109	62	9	0

262	277	S Melvin	1988	168	46	23	-10	0
242	278	J Ojeda	1988	90	25	16	-224	17
269	279	R Thompson	1988	1369	47	22	-5	0
252	280	C Bromley	1986	335	64	28	59	0
332	281	H Peterson	1984	22	22	15	0	0
284	282	K Pound	1983	65	50	41	85	0
256	283	D Leahy	1983	144	93	57	-70	0
279	284	V Arney	1981	534	92	51	-4	0
264	285	P Coles	1979	156	44	27	30	0
272	286	J Stevens	1978	209	37	20	29	0
308	287	G Greenwood	1974	70	22	17	130	3
300	288	J Dimech	1971	686	46	22	-124	1
263	289	S Olsen	1968	391	70	32	-2	0
294	290	J Skingsley	1966	104	36	21	53	0
295	291	D Nottage	1966	216	43	20	52	0
267	292	G Young	1966	906	117	57	2	0
314	293	D Cooke	1965	863	75	41	-100	1
266	294	P Watts	1965	439	140	90	27	0
304	295	H Reeves	1963	310	84	53	74	0
285	296	M O'Brian	1962	1011	92	43	-25	0
253	297	G Giacomini	1958	141	28	16	59	0
283	298	D Green	1958	206	90	48	4	0
325	299	D Gaitley	1957	615	55	24	34	0
298	300	M Reidy	1957	156	93	51	-81	0
268	301	J Norback	1956	268	61	26	-32	0
307	302	L Heard	1955	296	77	43	-78	0
278	303	R Schodel	1952	270	64	35	43	0
305	304	I Hunter	1949	88	24	15	0	0
321	305	I Brand	1943	979	40	18	-48	0
336	306	C Vilain Xiiii	1943	335	36	13	-90	0
302	307	D Jury	1942	146	25	9	-38	0
316	308	G Reilley	1942	206	52	21	9	0
227	309	A Urbano	1942	219	72	46	106	11
303	310	B Arliss	1940	1528	40	20	22	0
309	311	K Ham	1938	685	38	16	6	0
337	312	D Thirtle-Watts	1937	190	43	23	-3	0
343	313	S Dreyer	1937	124	21	9	5	0
311	314	M Tinker	1936	243	44	23	104	1
334	315	K Pickett	1935	52	20	9	-57	0
374	316	T Flexman	1932	140	48	29	-54	0
330	317	R Martin	1932	36	36	19	-32	0
378	318	E Brady	1930	147	23	14	-109	11
297	319	M Trefusis-Paynter	1930	236	67	34	-26	0
341	320	J Isaacs	1930	308	53	26	-37	0
344	321	A Hope	1930	80	20	5	-46	0
372	322	C Jackson	1928	746	41	19	-85	0
339	323	K Burt	1925	421	61	39	-15	0
310	324	C Leahy	1925	153	81	46	-54	0
306	325	J James	1924	90	37	21	19	0
361	326	G Keating	1924	405	68	30	-34	0
348	327	W Lotfi	1923	83	35	8	-7	0
315	328	F Thompson	1922	432	34	11	12	0
340	329	C Quinn	1921	450	136	68	-66	0
320	330	P Gunn	1920	228	90	37	2	0
335	331	R Ellis	1920	354	48	18	-31	0
439	332	T Sandstrom	1917	65	37	21	-80	0
373	333	P Young	1917	977	82	41	57	0

386	334	H Ezzat	1915	127	25	6	43	0
271	335	G Mohi	1915	146	89	45	59	0
342	336	I Shore	1914	226	43	22	49	0
323	337	D Studerus	1912	101	26	19	68	0
313	338	M Whitfield	1911	267	31	14	-14	0
357	339	J Mchardy	1911	519	153	80	-49	0
414	340	K Southern	1910	301	64	31	0	0
322	341	D Underhill	1910	588	31	18	-60	0
391	342	S Bowater	1909	175	31	11	-31	0
360	343	A Brookes	1909	373	65	37	-131	8
299	344	J Hodgett	1908	103	75	45	81	0
326	345	B Jennings	1906	270	143	67	54	0
470	346	D Turnbull	1906	26	20	10	0	0
376	347	J Saunders	1906	806	128	59	-14	0
367	348	T Parker	1905	129	40	16	-21	0
355	349	T Thornton	1905	118	42	17	-39	0
329	350	T Weston	1903	1427	94	39	-46	0
312	351	R Serrano	1902	126	28	16	-73	0
351	352	M Hamann	1901	161	64	30	8	0
371	353	S Leonard	1900	79	73	49	-39	0
364	354	C Mounfield	1899	332	24	8	-114	5
346	355	P Anderton	1899	182	20	12	63	0
319	356	F Alvarez-Sala	1898	77	28	20	-34	0
347	357	T Magin	1898	497	52	23	-72	0
317	358	G Freeman	1897	232	43	27	62	0
379	359	M Lewis	1897	230	81	43	-46	0
333	360	V Stilwell	1896	163	27	13	7	0
356	361	G Brennan	1892	67	30	14	48	0
324	362	J Williams	1892	182	25	12	17	0
301	363	A Clark	1891	67	20	11	32	0
369	364	A Reed	1891	74	25	17	7	0
346	365	P Anderton	1891	253	74	40	21	0
382	366	C Williamson	1890	41	41	21	-80	0
368	367	G Pitman	1890	569	40	24	19	0
440	368	R Carpenter	1888	89	22	12	-79	0
363	369	M Mckenzie	1888	43	30	16	-13	0
451	370	F Sarhan	1887	47	25	6	-88	0
353	371	B Rubock	1887	255	85	42	50	0
328	372	J Peman	1886	210	45	28	-87	0
467	373	R Channon	1885	38	23	15	-22	0
424	374	M Mcclure	1885	523	30	11	-6	0
366	375	E Zeh	1879	184	22	13	17	0
255	376	C Irwin	1878	39	22	14	24	0
402	377	M Fensome	1877	244	49	21	42	0
406	378	D Whyte	1877	74	58	19	23	0
403	379	D Williamson	1876	54	30	19	-26	0
419	380	D Boyd	1875	77	32	18	-50	0
400	381	M Cowman	1871	452	102	53	47	0
359	382	M Taylor	1870	143	59	37	-46	0
381	383	G Dickie	1869	143	56	22	-10	0
331	384	S Jackson	1869	153	54	32	82	0
410	385	M Mcnae	1867	109	36	15	-16	0
345	386	S Roberts	1866	560	84	38	-32	0
416	387	A Dymond	1865	662	111	40	-69	0
422	388	R Wootton	1864	416	38	16	-46	0
413	389	H Jansson	1864	992	148	57	19	0
482	390	M Hart	1859	89	20	7	-51	0

380	391	L Boman	1858	42	42	17	0	0
449	392	A Ramsis	1856	248	21	4	-126	4
349	393	G Mclean	1855	139	78	42	65	0
426	394	C Sharpe	1855	140	67	23	73	0
412	395	M Boys	1853	54	21	9	-49	0
396	396	E Rubock	1853	251	101	49	58	0
370	397	K Wright	1852	413	98	44	52	0
399	398	P Haydon	1852	186	76	27	44	0
325	399	D Gaitley	1852	224	35	15	12	0
393	400	S Martins	1851	120	22	13	-2	0
433	401	B Hollier	1851	42	37	21	77	0
441	402	M Myhrene	1848	174	49	19	-63	0
398	403	J Johnstone	1847	42	21	11	14	0
390	404	M Boeer	1845	472	52	20	17	0
362	405	A Miller	1845	907	142	73	-116	2
434	406	T Sparks	1844	241	57	27	41	0
475	407	J Thorp	1843	144	20	6	-1	0
365	408	R Parks	1842	102	86	46	42	0
377	409	K Magee	1842	199	80	46	-5	0
318	410	F Soto	1842	115	33	21	44	0
498	411	I Brown	1841	70	45	23	-94	7
397	412	A Hall	1839	823	31	9	-144	7
395	413	F Moir	1839	77	22	17	41	0
431	414	R Johnstone	1839	866	117	52	-70	0
408	415	T Meredith	1836	26	26	16	0	0
428	416	J Grieve	1835	235	47	21	-43	0
447	417	A Elfstrom	1835	44	33	20	17	0
405	418	D Cooper	1834	150	29	15	9	0
392	419	A Carpenter	1833	277	70	40	96	1
409	420	M Murphy	1833	205	22	10	39	0
420	421	R Templeman	1832	26	26	17	0	0
415	422	A Daniel-Dreyfus	1832	181	77	35	39	0
385	423	K Chynoweth	1828	366	41	27	52	0
404	424	L Dixon	1826	315	113	60	8	0
421	425	P Dodson	1825	67	30	17	5	0
384	426	E Burridge	1822	81	45	18	39	0
429	427	D Bull	1821	256	61	30	-36	0
438	428	J Greenwood	1819	48	23	16	112	1
401	429	R Keighley	1819	113	21	14	57	0
458	430	B Dawes	1817	107	22	9	3	0
493	431	M Adams	1815	73	30	9	-88	0
407	432	K Logan	1814	404	126	59	76	0
591	433	I Power	1814	30	30	18	20	0
411	434	C Merrington	1814	91	25	7	-4	0
429	435	D Bull	1814	376	84	49	86	0
459	436	B Williams	1813	136	47	21	-95	3
460	437	J Sim	1813	260	38	18	-1	0
465	438	C Heath	1812	322	84	39	-6	0
443	439	G Rebuelta	1811	279	45	28	-3	0
474	440	S Kingsborough	1811	139	27	10	-13	0
327	441	J Gumbrell	1810	117	65	24	244	46
427	442	G Thomas	1810	206	24	10	-15	0
464	443	F Vitty	1809	1345	77	41	-61	0
375	444	B Gomez	1809	54	29	17	47	0
383	445	P Gentle	1809	827	31	21	116	1
388	446	P Durkin	1808	79	57	41	50	0
354	447	P Hamilton	1808	132	45	32	110	1

490	448	H Denton	1807	104	72	33	-22	0
389	449	M Lindbergs	1807	226	41	24	20	0
499	450	B Piggott	1805	420	34	16	-69	0
599	451	M Isles	1804	30	30	14	24	0
461	452	B Mccausland	1803	212	55	33	17	0
476	453	F Guilloto	1802	68	22	13	-1	0
358	454	S Freimane	1801	149	23	14	67	0
450	455	S Anderson	1801	539	55	31	-5	0
466	456	A Allan	1801	98	36	19	0	0
418	457	P Brown	1800	370	67	26	62	0
454	458	M Bilton	1799	258	109	58	16	0
488	459	J Kermode	1798	525	56	25	9	0
452	460	S Marsh	1797	90	46	27	13	0
486	461	P Goldstraw	1797	198	63	32	-47	0
387	462	F Caballero	1795	59	30	16	90	0
417	463	G Flowers	1794	105	29	19	42	0
478	464	P Clift	1793	20	20	13	0	0
514	465	M Burger	1789	100	27	16	25	0
432	466	C Tacey	1789	493	38	22	47	0
473	467	J Cundell	1789	285	24	12	-46	0
472	468	K Terry	1788	131	38	20	31	0
444	469	R Christian	1787	221	50	25	10	0
480	470	R Bagni	1787	232	70	42	-79	0
495	471	C Eiffert	1786	35	25	14	-29	0
483	472	C Wood	1786	263	99	44	67	0
468	473	L Taylor	1786	276	65	39	25	0
503	474	J Pengelly	1784	42	24	11	-3	0
519	475	P Moore	1784	42	23	11	-69	0
394	476	M Bausa	1783	141	68	40	-40	0
423	477	A Usans	1780	303	35	20	-55	0
446	478	H Jackson	1780	55	45	23	67	0
501	479	K Eccles	1778	207	36	20	-80	0
510	480	N Westmore	1777	172	28	14	11	0
507	481	S Truman	1775	51	20	13	19	0
569	482	R Chatwin	1772	35	29	19	5	0
513	483	M Huxley	1772	200	49	26	-47	0
442	484	G Willson	1771	146	21	12	74	0
532	485	D Johnson	1768	102	21	8	-125	5
508	486	K Webb	1767	670	29	12	-1	0
437	487	R Peperell	1766	213	32	22	36	0
515	488	S Mcbride	1766	451	139	72	-77	0
469	489	F Mestanza	1764	50	39	27	112	4
494	490	A Huxley	1764	507	97	58	-112	3
481	491	R Carline	1762	243	130	62	5	0
566	492	R I'Anson	1761	67	35	20	-83	0
456	493	G Lopez De Carrizosa	1760	55	35	23	28	0
511	494	T Jansen	1759	46	29	17	71	0
504	495	J Ball	1758	209	30	19	63	0
445	496	W Munns	1757	173	54	23	112	10
492	497	K Tanguay	1757	21	21	10	0	0
453	498	D Walker	1756	58	20	12	58	0
521	499	G Vautier	1756	99	40	19	14	0
462	500	I Reed	1755	21	21	9	0	0
563	501	D Whitehead	1753	42	25	11	14	0
463	502	N Thomas	1753	102	40	16	75	0
489	503	A Woodhouse	1752	311	108	60	81	0
529	504	D Ball	1752	304	24	4	-51	0

497	505	A Graf	1752	137	59	19	58	0
471	506	R Godfrey	1751	342	33	16	34	0
457	507	J Skuse	1751	251	64	34	55	0
517	508	M Charlton	1749	70	29	12	28	0
512	509	B Mcalister	1749	265	76	27	-17	0
477	510	F Puerto	1748	238	31	19	-32	0
479	511	M Molina	1747	123	38	21	-5	0
545	512	N Pope	1745	466	41	16	2	0
435	513	B Brown	1745	116	68	30	46	0
518	514	D Pleasants	1745	57	22	10	32	0
559	515	C Brady	1744	95	27	15	2	0
496	516	S Polglase	1743	45	35	13	-92	1
455	517	G Mccausland	1743	29	25	14	0	0
502	518	G Taylor	1743	302	55	31	-59	0
516	519	H Cook	1743	154	30	16	-21	0
556	520	R Mounfield	1742	1240	90	28	-85	0
577	521	J Smith	1739	45	34	14	43	0
540	522	L Grant	1737	323	100	37	-12	0
522	523	T Farrell	1736	77	48	22	25	0
547	524	R Brand	1735	624	26	8	41	0
485	525	G Steiner	1734	157	39	13	33	0
543	526	N Connor	1732	48	24	11	22	0
528	527	R Pickvance	1732	52	52	26	22	0
526	528	G Fauske	1731	47	27	13	34	0
550	529	P Sim	1731	164	33	13	14	0
509	530	R Schworm	1731	21	21	11	0	0
425	531	I Fernandez-Prada	1730	77	36	18	76	0
565	532	C Wilkie	1730	49	25	12	23	0
448	533	T Freimanis	1728	148	25	12	38	0
555	534	M Buckley	1727	58	26	15	-30	0
505	535	P Christmass	1726	106	53	29	-37	0
553	536	A Henry	1724	145	31	10	-3	0
573	537	R Newsham	1723	843	54	24	-16	0
491	538	J Gartner	1722	67	28	14	88	0
583	539	A Frewin	1720	56	20	9	89	0
531	540	P Homer	1720	33	29	13	21	0
551	541	E Woodley	1716	31	31	10	51	0
548	542	H Denny	1714	198	61	22	-5	0
567	543	N Posselt	1714	208	64	22	12	0
582	544	C Stephens	1714	108	27	9	-23	0
533	545	B Wild	1713	220	36	14	-28	0
572	546	M Anderton	1711	49	25	11	-37	0
539	547	M Wroughton	1710	113	26	12	-58	0
484	548	J Kral	1710	100	22	15	102	2
584	549	R Cook	1708	28	24	13	0	0
604	550	J Beattie	1708	115	49	25	-52	0
542	551	H Rillie	1707	191	99	39	-47	0
534	552	P Lund	1706	59	23	10	-71	0
524	553	I Gutierrez-Trueba	1705	115	45	21	-47	0
561	554	K Collins	1704	102	22	12	-59	0
523	555	J Lynch	1702	109	45	17	-35	0
530	556	L Easton	1698	125	52	20	-92	1
431	557	R Johnstone	1698	734	112	45	10	0
562	558	M Sawers	1697	70	44	20	-108	1
574	559	K Connery-Albert	1697	69	24	10	-26	0
598	560	K Hume	1696	113	23	3	-198	3
546	561	M Manning	1696	156	63	28	-8	0

580	562	J Otte	1695	367	52	28	-116	14
560	563	C Spittal	1695	51	30	11	128	13
525	564	B Mcalary	1694	320	35	12	49	0
506	565	A Kralova	1691	137	39	17	92	1
575	566	M Romero	1691	47	37	21	-47	0
589	567	G Fulford	1690	47	20	7	57	0
500	568	O Baird-Gosling	1690	79	23	10	160	47
594	569	D Holland	1689	72	24	14	88	0
564	570	R Stroud	1687	254	42	19	4	0
585	571	T Duley	1687	36	25	10	34	0
487	572	A Rebuelta	1683	164	28	16	45	0
579	573	S Hoddy	1683	24	24	5	0	0
558	574	R Weaver	1682	189	37	9	3	0
603	575	M Thorne	1680	40	22	10	-9	0
601	576	P Donner	1680	139	29	18	4	0
557	577	E Montague	1678	150	54	25	-39	0
538	578	A Dask	1677	69	36	14	212	31
590	579	E Coles	1676	64	32	9	-1	0
626	580	F Low	1675	28	28	7	0	0
576	581	T Mcarthur	1674	198	67	20	-43	0
588	582	A Green	1673	55	25	10	37	0
571	583	P Markwell	1672	37	28	12	-17	0
605	584	D Hembrow	1672	130	40	13	-31	0
627	585	E Ross	1671	32	32	21	-31	0
554	586	A Lee	1671	245	28	15	72	0
600	587	G Benvie	1670	305	48	11	-86	0
520	588	V Olsen	1670	186	57	24	-16	0
593	589	J Bury	1670	27	27	9	0	0
541	590	K Millhouse	1669	87	41	10	-59	0
586	591	D Deadman	1669	89	25	12	23	0
552	592	P Tracey	1666	177	35	13	-46	0
607	593	D Buxton	1666	474	31	14	-83	0
535	594	G Trivett	1664	569	63	24	7	0
613	595	K Loane	1657	37	24	9	-48	0
549	596	G Kirkland	1656	451	21	11	26	0
570	597	P Paine	1654	571	46	22	30	0
602	598	J Gatchell	1646	100	78	28	79	0
622	599	S Mckessar	1646	52	34	15	9	0
608	600	B Pendry	1646	54	26	17	48	0
617	601	L De Gortazar	1645	282	41	21	-61	0
606	602	M Wilson	1643	112	34	12	-15	0
536	603	P Pekaar	1641	57	32	17	177	11
616	604	A Wilkie	1641	62	25	10	102	3
637	605	P Nuttall	1632	27	21	8	0	0
619	606	A Murray	1632	59	23	10	-25	0
632	607	J Taylor	1632	55	21	8	20	0
597	608	R Jenkins	1630	379	69	33	32	0
544	609	Y Shaw	1629	78	59	31	97	32
609	610	S Vorel	1628	91	35	10	42	0
643	611	K Johnston	1627	175	68	28	7	0
648	612	A Foott	1626	55	27	13	-68	0
640	613	C Piercy	1624	519	36	9	-105	1
618	614	A Kukla	1623	20	20	8	0	0
644	615	M Vainio	1623	42	24	8	44	0
587	616	S Huber	1623	90	28	17	100	1
642	617	K Small	1623	61	50	11	7	0
668	618	R Tombleson	1623	24	24	16	0	0

610	619	J Boucher	1620	87	60	26	-50	0
658	620	K Woodward	1620	85	32	10	-41	0
635	621	M Salazar	1620	218	34	14	-49	0
620	622	T Burt	1620	278	41	17	-12	0
537	623	W Hall	1618	139	20	11	6	0
595	624	C Smith	1617	85	75	40	163	16
625	625	A Wright	1616	132	42	15	56	0
615	626	M O'Neale	1616	250	34	16	-44	0
614	627	A Dennis	1615	76	26	10	12	0
665	628	M Webb	1613	590	29	7	-22	0
568	629	J Doepel	1610	156	75	29	111	9
592	630	D Robinson	1606	97	24	15	64	0
639	631	R Sanville	1601	76	21	7	-14	0
621	632	K Molyneux	1599	44	44	18	33	0
611	633	A Perez-Barbadillo	1599	59	26	15	64	0
656	634	J Cook	1599	248	86	30	77	0
612	635	B Medina	1595	26	23	10	0	0
703	636	B Elzaburu	1593	31	31	12	35	0
679	637	M Robles	1592	35	23	15	40	0
681	638	C Evans	1589	72	30	10	-6	0
581	639	R Lentz	1582	21	21	7	0	0
664	640	V Saunders	1580	173	37	9	-86	0
649	641	E Buxton	1579	644	68	26	-14	0
578	642	C Perez Nogueras	1575	113	30	17	151	36
673	643	K Melksham	1575	51	45	16	-31	0
641	644	N Melksham	1574	119	58	26	-23	0
646	645	E Hannay	1572	156	22	16	85	0
645	646	M Frayne	1572	60	30	13	83	0
596	647	Z Plavins	1571	303	46	20	-8	0
623	648	J Tewson	1570	42	42	17	83	0
628	649	S Howlett	1570	52	47	20	39	0
659	650	R Skidmore	1569	42	36	15	1	0
655	651	K Jones	1568	42	38	12	27	0
647	652	R Pimlott	1566	353	30	11	25	0
624	653	L Sexton	1564	75	31	10	162	21
683	654	P Dennis	1562	92	43	14	-224	12
662	655	J Collier	1561	625	59	21	27	0
661	656	B Perkins	1561	101	31	14	7	0
638	657	M Burguete	1559	60	30	11	7	0
675	658	K Le Poidevin	1557	41	41	8	89	0
650	659	W Drake	1557	162	65	24	17	0
689	660	A Widdison	1556	179	54	14	-64	0
680	661	J Carbone	1556	26	26	13	0	0
653	662	J Pongratz	1556	311	37	17	45	0
667	663	J Powis	1555	462	84	30	113	6
546	664	M Manning	1554	101	49	16	23	0
678	665	V Harding	1543	385	21	5	-82	0
670	666	J Edwards	1543	469	37	7	-137	5
634	667	T Dunbar	1542	36	36	12	-52	0
631	668	C Ariza	1542	59	24	16	117	3
672	669	C Monzon	1541	102	37	17	-26	0
666	670	M Marcos	1539	127	86	24	4	0
629	671	A Savinovs	1539	270	52	20	-1	0
698	672	C Reynolds	1532	584	83	31	7	0
671	673	D Giles	1532	49	49	19	28	0
633	674	R Dart	1527	196	62	26	5	0
660	675	V Harlinskis	1525	310	39	17	7	0

663	676	C Kirkland	1523	58	22	10	-4	0
652	677	E Bassett	1518	31	31	10	48	0
676	678	W Freeman	1518	290	52	17	38	0
654	679	S Echevarria	1518	114	23	6	8	0
704	680	U Greder	1517	115	58	16	-207	22
677	681	K Jeffery	1512	202	49	19	20	0
657	682	M Shewry	1509	71	23	6	117	14
690	683	M Cussell	1505	40	21	9	39	0
687	684	S I'Anson	1505	64	28	11	44	0
705	685	R Donner	1504	106	20	5	-148	15
457	686	J Skuse	1500	57	21	6	19	0
696	687	M Maldonado	1493	143	27	7	-190	23
691	688	P Knight	1491	284	72	26	49	0
692	689	N Greig	1490	255	68	21	-74	0
701	690	P Gonzalez De Aguilar	1490	38	29	16	82	0
712	691	R Barter	1487	83	20	1	-218	24
699	692	J Brand	1483	54	50	17	-10	0
706	693	G Brent	1482	329	93	25	-150	5
700	694	L Portela	1476	39	20	8	28	0
674	695	A Lucke	1475	25	20	4	0	0
694	696	J Dyer	1474	101	55	18	11	0
695	697	M Guardiola	1472	89	27	10	36	0
685	698	I Kleimanis	1469	242	39	22	58	0
697	699	K Mcloughlin	1463	30	30	13	-57	0
669	700	E Paravicini	1461	81	24	5	151	6
708	701	R Keech	1451	21	21	8	0	0
636	702	W Pritchard	1435	39	35	11	79	0
713	703	A Greder	1435	66	30	9	5	0
684	704	J Jago	1434	82	82	17	144	41
686	705	S Harlinska	1432	216	31	14	-37	0
682	706	N Bauerova	1427	65	22	7	115	16
709	707	M Bume	1425	20	20	6	0	0
630	708	S Pendry	1424	23	23	5	0	0
718	709	J Fowler	1424	70	49	13	157	5
688	710	L Usane	1420	208	33	18	12	0
725	711	S Green	1419	25	25	8	0	0
714	712	D Renedo	1418	150	23	5	-44	0
707	713	R Dunders	1402	45	33	18	107	1
702	714	V Hilton	1400	62	21	11	34	0
721	715	M Robinson	1384	50	25	3	70	0
710	716	I Florido	1375	233	35	10	15	0
723	717	D Bonnitcha	1374	65	20	7	93	1
729	718	P Lester	1371	51	30	10	105	3
656	719	J Cook	1371	84	33	8	62	0
719	720	A Usane	1370	222	21	10	-18	0
683	721	P Dennis	1363	65	40	8	47	0
568	722	J Doepel	1356	43	33	10	25	0
716	723	J Stafecka	1345	212	29	16	27	0
722	724	A Reisners	1345	96	24	11	30	0
728	725	L Toms	1344	20	20	5	0	0
711	726	D Brencena	1317	49	33	16	-11	0
717	727	M Henderson	1317	65	39	12	259	20
726	728	C Hodges	1314	49	28	9	107	1
731	729	B Clark	1289	32	20	0	64	0
724	730	N Reisners	1243	73	27	12	229	29
730	731	M Lauer	1060	28	28	3	0	0