Estimating the Effect of Match Schedule on FIRST Tournament Rankings

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Overview:

This paper presents a methodology to estimate the effects of match schedule on team rankings in FIRST tournaments.

First, team offensive power is estimated using the well established Offensive Power Rating (OPR) parameter estimation. Least Squares (LS) or Minimum Mean Squared Error (MMSE) techniques can be used to estimate the OPR parameters.

Second, tournament matches are modeled with each alliance score being the sum of the OPR values for each alliance member plus additive noise which represents match randomness that cannot be captured by the OPR estimates. Overall match variance and OPR variance are measured from the actual tournament data.

Third, given the match model, estimates are computed for the following:

A. The expected average number of wins for each team given the specific match schedule used in the tournament.
B. The expected average number of wins for each team given a random tournament match schedule with the same distribution of team OPRs as that measured from the given tournament.
C. The expected average number of wins for an average team given the specific match schedule used in the tournament.

Fourth, the different estimates are computed and discussed for a variety of FIRST Tech Challenge (FTC) tournaments. The same techniques can be applied to FIRST Robotics Competition (FRC) tournaments, though that is not done in this paper.

Fifth, the validity of the different model assumptions is investigated and discussed.

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Introduction

FIRST is a non-profit organization that sponsors four levels of robotics competitions for youth: FIRST Robotics Competition (FRC), FIRST Tech Challenge (FTC), FIRST Lego League (FLL) and Junior FIRST Lego League (JrFLL).

In FRC and FTC, teams build robots and compete in matches where alliances of multiple robots face off against each other. In FRC the alliances have 3 teams and in FTC the alliances have 2 teams. The remainder of the discussion in this paper focuses on the analysis of FRC 3 v. 3 matches but the analysis can be easily modified to accommodate FTC 2 v. 2 matches.

During a tournament, over a season, and from season to season, teams play many matches. This paper investigates the effects of particular tournament match schedules on the expected number of wins for a particular team at a given tournament. Techniques used in the paper can be used to estimate how favorable or unfavorable a particular team's match schedule was in a particular tournament and how that affected the team's tournament ranking.

Notation and Conventions

Scalars are shown italicized like *R*. Vectors and matrices are shown in bold like **O**. Vector and matrix transpose is denoted with a trailing apostrophe " ' " like **O**'.

Measurements of the offensive contribution of a team are indicated by some form of *O* or **O**. Offensive contributions usually have an average, *Oave*, of ⅓ of the average match score in a tournament.

Measurements of the defensive contribution of a team are indicated by some form of *D* or **D**. Defensive contributions described in this paper *usually* have an average, *Dave*, of 0, and *usually* a positive contribution corresponds to a positive outcome for a team (i.e., a *D* of +5 means that a team's defensive contribution is 5 points better than average).

Measurements of the contribution of a team to its alliance's overall Winning margin (i.e., their alliance's score minus their opposing alliance's score) are indicated by some form of *W* or **W**. Winning margin contributions usually have an average, *Wave*, of 0.

Measurements of the Combined contribution of offense and defense of a team to its alliance's performance are indicated by some form of *C* or **C**. Combined contributions in this paper are usually a measure of **O** + **D**, and as a result Combined contributions usually have an average *Cave* = *Oave*. Combined contributions are often related to the Winning margin contributions by the relationship **W** = **C** - *Oave*.

Parameter estimates (scalar or vector) are underlined, like $\underline{\mathbf{O}}_{ave}$.

MMSE-based parameter estimates (scalar or vector) are "hatted," like $\widehat{O}$.

Estimating Team Offensive Power

This section is largely taken from the paper "An Overview and Analysis of Statistics used to Rate FIRST Robotics Teams" slightly modified for the two team alliances used in FTC matches.

Full Model Equation for Offense

Each FTC match produces two outcomes: the Red alliance final score and the Blue alliance final score[1]. In most seasons, the alliance with the larger score is also declared the match winner.

The linear match model used in this paper is:

$$R = (O_i + O_j) - (D_l + D_m) + N_r$$

$$B = (O_l + O_m) - (D_i + D_j) + N_b$$

Teams i and j are on the Red alliance and teams l and m are on the Blue alliance. *Oi* is the offensive contribution of team i and *Di* is the defensive contribution of team i. In both cases, a positive value is beneficial to a team: a larger positive value of *Oi* for team i means that their alliance will score more points, and a larger positive value of *Di* means that their opposing alliance will score fewer points. *R* and *B* are the final Red and Blue alliance scores.

For FRC matches, the equations are similar except there are 3 *O* and *D* terms for each alliance instead of 2.

Nr and *Nb* are noise. These noise terms can model either match-to-match variations in noise or noise due to nonlinearities in actual match play. The match noise is modeled in this paper as having constant variance from match to match. This can be viewed either as variation due to individual match randomness or as constant variation produced by teams themselves (e.g., drivers not driving exactly the same way, etc.). It may be of interest to model the match noise as being produced by the teams and the team-based match noises NOT all having the same variability (e.g., team 1 always scores 1000 points or 0 points while team 2 always scores 10 points or 0 points). This paper does not address this question.

In vector-matrix form, the above equations for teams 1-4 can be written as

[1] Outcomes on parts of the matches may also be available, like Red and Blue autonomous scores, teleop scores, end-game scores, penalty scores, etc. Most of the analyses in this paper can also be applied individually to these scores as if they were final match scores, and can be used to evaluate the performance of teams in these subareas as well. The FTC android app "FTC2016" does exactly that for FTC tournaments.

$$\begin{bmatrix} R \\ B \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 & | & 0 & 0 & -1 & -1 \\ 0 & 0 & 1 & 1 & | & -1 & -1 & 0 & 0 \end{bmatrix} \begin{bmatrix} O_1 \\ O_2 \\ O_3 \\ O_4 \\ - \\ D_1 \\ D_2 \\ D_3 \\ D_4 \end{bmatrix} + \begin{bmatrix} N_r \\ N_b \end{bmatrix}$$

This form can be expanded for a full tournament with m matches and t teams. Define **Ar** as the m x t matrix with i,jth element equal to 1 if team j is on the Red alliance in match i and 0 otherwise, **Ab** as the m x t matrix with i,jth element equal to 1 if team j is on the Blue alliance in match i and 0 otherwise, **Mr** as the m-length vector of the Red alliance scores, and **Mb** as the m-length vector of the Blue alliance scores. Then,

$$\begin{bmatrix} \mathbf{M}_r \\ \mathbf{M}_b \end{bmatrix} = \left[\begin{array}{c|c} \mathbf{A}_r & -\mathbf{A}_b \\ \mathbf{A}_b & -\mathbf{A}_r \end{array}\right] \begin{bmatrix} \mathbf{O} \\ \mathbf{D} \end{bmatrix} + \begin{bmatrix} \mathbf{N}_r \\ \mathbf{N}_b \end{bmatrix}$$

or

$$\mathbf{M}_o = \left[\mathbf{A}_o \middle| -\mathbf{A}_d\right] \begin{bmatrix} \mathbf{O} \\ \mathbf{D} \end{bmatrix} + \mathbf{N}_o$$

“Full Model Equation for Offensive Scores”

Mo is the full vector of offensive match scores, **Ao** is the matrix describing which teams played offense producing a given match score (with an i,jth element of 1 if team j was on offense leading to match score i), **Ad** is the matrix describing which teams played defense producing a given match score (with an i,jth element of 1 if team j was on defense leading to match score i), **O** is the vector of team offensive contributions, **D** is the vector of team defensive contributions, and **No** is the full vector of offensive match noise values. **Mo** and **No** are 2m-length vectors, **Ao** and **Ad** are 2m x t matrices, **O** and **D** are t-length vectors.

Given a model with values of **O** and **D**, exactly the same match outcomes are produced with the related model **O**+K and **D**+K, where K is an arbitrary scalar constant. As a matter of convention, this paper normalizes models like this or estimates of the parameters **O** and **D** by computing the mean of all of the elements of **D** and then subtracting that mean from all elements of **O** and **D**. This produces the interpretation of elements of **O** as the expected contribution a team makes to its alliance's match scores when playing against average defense, and the interpretation of elements of **D** as the expected contribution a team makes against its opposing alliance's match scores, relative to the average defense. This is discussed further in later sections.

Full Model Equation for Winning Margin

Similarly, a linear model for the winning margin *R-B* can be formed by taking the difference of the previous equations as

$$R - B \;=\; (\,(O_i + D_i) \;+\; (O_j + D_j)\,) \;-\; ((O_l + D_l) \;+\; (O_m + D_m)\,) \;+\; N_r - N_b$$

If a team's contribution to their winning margin is defined as $W_i = (O_i - O_{ave}) + D_i$, then the expression can be similarly rewritten as:

$$[R - B] = [1 \quad 1 \quad -1 \quad -1] \begin{bmatrix} W_1 \\ W_2 \\ W_3 \\ W_4 \end{bmatrix} + [N_r - N_b]$$

The *Oave* terms are included to make **W** have zero mean, and they cancel each other out in the above equation. For a full tournament, the matrix-vector equivalent equation becomes

$$\mathbf{M}_r - \mathbf{M}_b = \left(\mathbf{A}_r - \mathbf{A}_b\right)\mathbf{W} + \left(\mathbf{N}_r - \mathbf{N}_b\right)$$

or

$$\mathbf{M}_w = \mathbf{A}_w \mathbf{W} + \mathbf{N}_w$$

"Full Model Equation for the Winning Margin"

Mw = **Mr** - **Mb** is the vector of winning margins with elements that are positive if Red won a match and negative if Blue won. **Aw** = **Ar** - **Ab** is a matrix describing which teams played in a given match (with i,jth element of 1 if team j was on Red in match i, -1 if team j was on Blue in match i, and 0 otherwise), **W** is the vector of winning margin contributions, and **Nw** = **Nr** - **Nb** is the vector of winning margin noise values. If **Nr** and **Nb** are independent and identically distributed, elements of **Nw** have twice the variance of elements of **No**.

Mw and **Nw** are m-length vectors, half the size of the corresponding **Mo** and **No** vectors. **Aw** is an m x t matrix, half the size of the corresponding **Ao** and **Ad** matrices.

Estimating Model Parameters

This section describes the different methods that are used to estimate different sets of model parameters. Their strengths and weaknesses are evaluated and discussed in following sections.

Offensive Power Rating (OPR) - Least Squares (LS)

A team's average match score can be artificially increased if that team happens to play with stronger teams than average or artificially decreased if that team happens to play with weaker teams than average.

One way to correct for alliance partner strength is by finding the values of **O** in the model for **Mo** that minimize the sum of the squared errors between the actual match scores and the match scores predicted by the model, which is equivalent minimizing **No' No**. *This assumes that the defensive contribution **D** is either 0, much smaller than **No**, or simply incorporated in **No** as additional noise.* This is like using the simplified model for **Mo** with **D**=0 shown below:

$$\mathbf{M}_o = \mathbf{A}_o\mathbf{O} + \mathbf{N}_o$$

"Partial Model Equation for Offense"

Finding the value of **O** that minimizes the squared error in a model where **D**=0 is a simple least squares problem, and the solution is

$$\underline{\mathbf{O}}_{opr} = \left(\mathbf{A}_o'\mathbf{A}_o\right)^{-1}\mathbf{A}_o'\mathbf{M}_o$$

Offensive Power Rating (OPR) - Minimum Mean Squared Error (MMSE)

In the previous section, the unknown OPR parameters were assumed to be constants that could take any value. If the unknown parameters are instead modeled as random variables themselves coming from a particular random distribution, improved estimation can be achieved using MMSE parameter estimation techniques. Wikipedia has a good overview of MMSE Estimation.

In particular, if the underlying elements of **O** have mean *Oave*= 1/2 of the average match score and variance σ_o^2 and the elements of the match score noise are zero mean and have variance σ_n^2, then the parameter estimation solution for OPR using MMSE techniques becomes

$$\underline{\hat{\mathbf{O}}}_{opr} = \left(\mathbf{A}_o'\mathbf{A}_o + \frac{\sigma_n^2}{\sigma_o^2}\mathbf{I}\right)^{-1} \mathbf{A}_o'(\mathbf{M}_o - 2O_{ave}) + O_{ave}$$

As the number of matches in a tournament gets large, the two parameter estimates approach each other. The MMSE techniques are better at predicting underlying offensive power early in tournaments when only a few matches have been played.

Modeling Tournament Matches

The remainder of this paper uses OPR estimates to model matches. The following model assumptions are made:

1. That the underlying match noise that cannot be modeled by the OPR estimates can be modeled reasonably well by a normal/ Gaussian distribution.
2. That the distribution of the OPR values themselves for teams in a tournament can be modeled reasonably well by a normal/ Gaussian distribution.
3. That defensive contributions are negligible and may be ignored.

As with all model assumptions, these conditions may or may not hold and the degree to which they hold may affect the conclusions drawn. The validity of these assumptions is studied in one of the final sections of this paper.

If defensive contributions are ignored, the model for the winning margin becomes

$$R - B = (O_i + O_j) - (O_l + O_m) + N_r - N_b$$

Modeling a Match with Known Teams

If all 4 teams are known and all 4 OPR values are known, then the match winning margin is modeled as a normally distributed random variable with

mean = $(O_i + O_j) - (O_l + O_m)$, and

variance = $2\sigma_m^2 - 4\sigma_o^2$

where σ_m^2 is the variance of the individual alliance match scores and σ_o^2 is the variance of the OPR values taken across all of the teams in the tournament. The factor of 2 arises because the noise is the difference between the red and blue match scores, and the factor of 4 arises because there are 4 teams involved in the match. For FRC matches, this factor would be 6 instead of 4.

Modeling a Match with Unknown, Random Teams

On the other hand, if only Oi is known for team i and the team is playing a match with 3 random teams with 3 OPR values taken randomly from a normal distribution with mean *Oave* and variance σ_o^2 , then the match winning margin is modeled as a normally distributed random variable with

mean = *Oi* - *Oave* , and

variance = $2\sigma_m^2 - \sigma_o^2$

Estimating Expected Numbers of Wins in Different Tournament Scenarios

For a given tournament, the following sections require that the following values be computed:

1. The OPR estimates for all teams in the tournament.
2. σ_m^2, the variance of the individual alliance match scores.
3. σ_o^2 , the variance of the OPR values taken across all of the teams in the tournament.

The cumulative distribution function (CDF) of a normally distributed random variable is defined as

$$\Phi(x) \;=\; \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-t^2/2}\, dt$$

and is used in subsequent sections.

A: Using the specific teams and the specific match schedule used in the tournament

With a particular match schedule, a team's probability of winning a particular match can be estimated as $\Phi\left(\frac{m}{\sigma}\right)$, where

m = $(O_i + O_j) - (O_l + O_m)$, and

$$\sigma^2 = 2\sigma_m^2 - 4\sigma_o^2.$$

This can be computed for each match for team *i* and summed to estimate the number of wins team *i* will win on average in this tournament with this match schedule. This can be computed for all teams in a tournament to predict general rankings.

B: Using the specific teams and a random tournament match schedule

With a random match schedule, a team's probability of winning a particular match can again be estimated as $\Phi\left(\frac{m}{\sigma}\right)$, but now where

m = *Oi* - *Oave*, and

$$\sigma^2 = 2\sigma_m^2 - \sigma_o^2.$$

Note that this is only a function of general tournament parameters and the individual team's OPR value *Oi*. This means that these "B" estimates have the same rank order as the underlying OPR estimates (i.e., the team with the highest OPR will have the highest "B" estimated number of wins, as the team that can score the most points should have the highest number of wins with a random match schedule).

Comparing the "A" and "B" estimates provides a way of estimating how the particular tournament match schedule helps or harms a particular team. If the "A" estimate is greater, then the team is paired with stronger partners and/or weaker opponents and the match schedule helps the team overall compared to a random match schedule. Conversely, if the "B" estimate is greater, then the team is paired with weaker partners and/or stronger opponents.

C: Using an average team and the specific match schedule used in the tournament

With a particular match schedule, an *average* team's probability of winning a particular match can be estimated as $\Phi\left(\frac{m}{\sigma}\right)$, where

m = $(Oave + O_j) - (O_l + O_m)$, and

$$\sigma^2 = 2\sigma_m^2 - 4\sigma_o^2$$

This can be computed for each match for team *i* and summed to estimate the number of wins an average team will win on average in the match schedule for team *i* tournament with this match schedule.

Comparing the “A” and “C” estimates provides a way of estimating how many more wins each team has compared to the number of wins an average team would have with the same schedule.

Comparing the “C” estimate with the number of matches played per team/2 also provides a way of estimating how many wins the particular schedule would help or harm the average team with this schedule. For example, in a tournament where each team plays 9 qualifying matches, the average team with the average schedule would be expected to win 4.5 matches. If the “C” estimate for a particular team is 5.5, that signifies that the schedule is “favorable” by 1 win to an average team (i.e., the schedule “gives the average team 1 extra win”). Conversely, if the “C” estimate is 3.5, that signifies that the schedule is “unfavorable” by 1 win to an average team (i.e., the schedule “costs the average team 1 win”).

Non-obvious effects of match schedule on different types of teams

It is possible for a match schedule to help an average team while simultaneously harming a very bad or very good team, or vice versa!

For example, imagine a match schedule where, for 8 of 9 matches, a team’s alliance partner is expected to score 50 points more than average while the opposing alliance is average but in the 9th match a team’s alliance partner is expected to score 400 points less than average(!).

An average team would benefit from this schedule. For a random schedule, an average team would have a 50% chance of winning every match (4.5 wins expected overall) while the same average team with this schedule might have a 75% chance of winning the first 8 matches and a 0% chance of winning the final match (6 wins now expected overall)!

However, imagine a team that has an OPR 200 points above average. For this team, a random schedule might have this team have a 95% chance of winning all 9 matches (8.55 wins expected overall), but with this schedule the team is now favored to win the first 8 matches with a 96% chance but now has only a 5% chance to win the final match (7.73 wins expected now).

Because of the nonlinearity in the CDF function, a particular schedule can have different results on different types of teams.

Evaluating the Estimates from Actual Tournament Data

This section presents the results of these estimates for some real-world FTC tournaments.

2016 FTC East Super Regional Hopper Division

Ftc: /2016EastHopper

Teams = 36, Matches = 81, Matches Per Team = 2.250

Team#	Wins	A	B	C	Team Name
8390	9.000	7.363	6.492	5.594	Nerd Herd
7314	8.000	6.476	6.611	4.589	Sab-BOT-age
8221	8.000	7.497	7.839	4.928	Cubix3
10392	7.000	4.894	4.698	4.741	The Rolling Drones
8528	7.000	5.043	4.068	5.398	Rhyme Know Reason
4347	6.000	6.959	7.097	3.768	NanoGurus
3415	6.000	6.178	4.482	6.192	Lancers
5421	6.000	5.435	4.235	5.690	RM'd and Dangerous
6055	6.000	5.901	5.963	4.685	GearTicks
6040	6.000	5.175	4.929	4.740	Canton Robodogs
8619	6.000	5.238	4.468	5.265	Cerebrum Bellatorum
7117	6.000	5.817	4.604	5.734	The Blockheads
18	6.000	4.372	4.048	4.786	The Techno Chix
7164	5.000	4.660	5.457	3.846	Falcon Bots
4029	5.000	6.628	7.177	4.075	2 Bits and a Byte
8645	5.000	5.615	6.078	4.439	Robotic Doges
248	5.000	3.594	4.679	3.444	Fatal Error
7393	4.000	5.696	6.083	4.142	electron Volts
7486	4.000	4.635	4.269	4.843	Suffern's Team Erebor
4486	4.000	4.748	5.615	3.671	Mad Science
8509	4.000	4.220	4.041	4.625	STEEL Serpents
3371	4.000	3.029	4.073	3.422	Botley Crue
6899	4.000	2.967	3.474	4.001	Blue Bots
4137	4.000	3.665	3.397	4.772	Islandbots
9927	4.000	3.985	3.268	5.021	The MidKnight Magic Too!
9372	3.000	4.476	5.209	3.798	Standard Model
6341	3.000	3.159	3.811	3.842	IBEX
5017	3.000	3.614	3.855	4.182	RoboEpic
5163	2.000	2.792	3.390	3.691	Flying Dragon
8702	2.000	3.575	2.477	5.272	Grey Jedi
6029	2.000	2.600	3.525	3.443	TEAM ROBOWIZ
9845	2.000	2.407	1.810	5.147	Robominions
4096	2.000	1.716	2.047	3.961	T-10 (T minus 10)
4286	2.000	2.543	1.677	5.434	Dragonoids
5485	1.000	3.880	3.602	4.916	GorillaBots
6527	1.000	1.449	2.909	2.826	North Robotics

A = expected # of wins for this team with this schedule

B = expected # of wins for this team with an average schedule

C = expected # of wins for an average team with this schedule

4.5 = expected # of wins for an average team with an average schedule

Discussion

- Column B again shows the expected number of wins for a team with a random schedule, which is a monotonically increasing function of that team's OPR. The teams with the highest OPRs were Cubix3, 2 Bits and a Byte, and Nanogurus. They ended up 3rd, 15th, and 6th respectively. Cubix has disconnection issues in 2 matches that led to 1 match loss. 2 Bits and a Byte had mechanical issues in some matches but scored a huge amount of points when their robot was working successfully. Nanogurus had a particularly unfavorable match schedule (3.7 wins expected for an average team vs. 4.5 for a random schedule)

- Nerd Herd, Rhyme No Reason, Lancers, RMed and Dangerous, and Blockheads had favorable match schedules that assisted in their high rankings.

- Nerd Herd and Cubix3 were the only two teams predicted to win more than 7 matches on average with the given tournament schedule. Nerd Herd was ranked 5th in OPR but had an advantageous schedule that bumped them from a 6.5 win team to a 7.4 win team. Cubix3 was ranked 1st in OPR but had a schedule that dropped them from a 7.8 win team to a 7.5 win team.

- What is not measured is reliability. For example, Nerd Herd scored consistently throughout the tournament but could not produce super-high scores by themselves. But by being reliable, with a favorable match schedule, and with favorable luck in individual matches, they were able to win all 9 matches in this particular tournament even though, on average, they were only estimated to win 7.4 matches if the tournament was repeated many times. In contrast, Cubix3 could produce the top scores in the tournament's qualifying matches but suffered from disconnection issues that cost them 1 win in qualifying matches and 2 wins in elimination rounds.

2016 FTC East Super Regional Tesla Division

Ftc: /2016EastTesla

Teams = 36, Matches = 81, Matches Per Team = 2.250

Team#	Wins	A	B	C	Team Name
5916	9.000	7.801	7.364	5.663	BoBots
8644	8.000	7.865	8.206	3.904	The Brainstormers
4318	8.000	7.051	5.873	5.893	Green Machine Reloaded
6081	7.000	6.718	7.243	3.890	i2r robotics
7350	7.000	6.000	4.577	5.924	Watt's NXT?
4082	7.000	5.967	5.575	4.989	RoboSpartans
8681	7.000	5.544	4.363	5.675	A Few Loose Screws
7149	6.000	3.988	3.746	4.807	EHTPAL ENFORCERS
9794	6.000	5.667	4.018	6.095	Wizards.exe
7423	6.000	4.748	3.926	5.307	Flaming Phoenix
7988	5.000	4.391	5.520	3.266	hound bots II
5069	5.000	4.764	4.674	4.603	Robogamers
8574	5.000	4.399	4.425	4.476	WeByte
6347	5.000	5.662	6.238	3.770	Geared Up
10358	5.000	4.192	5.099	3.561	Squatch Watch
7182	5.000	2.523	4.364	2.653	Mechanical Paradox
6955	5.000	4.328	3.876	4.840	Robovines
3397	5.000	3.057	2.511	5.336	Essex Robotics
6051	4.000	5.658	5.782	4.438	Quantum Mechanics
2818	4.000	5.544	5.265	4.852	G-FORCE
5484	4.000	4.695	5.618	3.673	Enderbots
8297	4.000	5.429	5.082	4.926	Geared UP!
9901	4.000	3.687	3.069	4.993	Techie Titans
8498	4.000	3.080	2.642	4.917	The Evil Purple Sox
6700	3.000	3.469	4.221	3.690	X-BOTS
3737	3.000	3.277	3.682	4.079	Hank's Tanks
9371	3.000	4.152	4.876	3.828	General Relativity
5169	3.000	2.818	4.116	3.170	Watt's Up?
121	3.000	3.166	3.365	4.157	Rhode Rage
10815	3.000	4.338	2.780	6.148	Westerly Bulldogs
6037	3.000	4.077	3.053	5.493	WAGS
4924	2.000	4.228	4.136	4.579	Tuxedo Pandas
4107	2.000	2.595	3.101	3.913	MohonBots
4419	1.000	2.780	3.274	4.082	Pokebots
8526	1.000	3.244	2.768	4.913	Aluminum Avian Antics
4244	0.000	1.097	2.206	2.929	Big Bertha

A = expected # of wins for this team with this schedule
B = expected # of wins for this team with an average schedule
C = expected # of wins for an average team with this schedule
4.5 = expected # of wins for an average team with an average schedule

Discussion

- Top teams Bobots and Green Machine Reloaded were strong teams helped by their match schedules, while top teams Brainstormers and i2robotics were strong teams hurt by their match schedules.

- Of particular interest was match 64 which pit Bobots against Brainstormers. Bobots was with Watt's NXT (a 4.6 win team with an average schedule) while Brainstormers was with Hanks Tanks (a 3.7 win team with an average schedule). This match alone was probably a strong determinant in Bobots having a more favorable schedule than Brainstormers, and it was the only match lost by Brainstormers which led to a 2nd seed finish instead of a 1st seed finish.

- Comparing the 3rd and 4th seeds, Green Machine Reloaded was a strong 5.9 win team that was raised to be a 7.1 win team by a favorable schedule, while i2robotics was a very strong 7.2 win team that was dropped to a 6.7 win team by an unfavorable schedule.

Overall across both Hopper and Tesla divisions, the match schedule for an average team (column C) ranged from 2.65 (Mechanical Paradox, the worst schedule for an average team to have) to 6.12 (Lancers, the best schedule for an average team to have). This shows that a range of 3.5 wins in a 9 team tournament could be due to match schedule alone.

2016 FTC World Championship Edison Division

Ftc: /2016WorldsEdison
Teams = 64, Matches = 144, Matches Per Team = 2.250

Team#	Wins	A	B	C	Team Name
5916	8.500	6.318	5.244	5.541	BoBots
6137	8.000	6.827	6.890	4.595	RoBowties
4029	7.000	6.889	7.419	3.628	2 Bits and a Byte
11044	7.000	5.463	4.556	5.409	PML30-Y
5220	7.000	7.250	6.053	6.301	RoboKnights 5220
8221	7.000	8.007	7.699	5.523	CUBIX^3
3781	7.000	6.911	6.973	4.323	Westlake Pi-Rho Maniacs
6299	7.000	6.243	6.230	5.010	ViperBots QuadX
5975	7.000	5.712	4.743	5.485	CYBOTS
5385	7.000	5.450	5.546	4.761	Enigma Riddlers
7242	7.000	5.397	3.511	6.137	RoboCats Delta Team
7655	6.500	5.523	6.387	3.564	The Q is Silqent
8644	6.000	6.352	6.346	4.187	The Brainstormers
7172	6.000	4.811	5.266	4.067	Technical Difficulties
6981	6.000	4.734	5.308	3.797	Hortonville Robotics
4997	6.000	5.899	6.032	4.642	Masquerade
10889	6.000	4.998	4.366	5.107	ROBOTRIX
3537	6.000	7.003	6.060	5.609	The MechaHampsters
3486	6.000	4.720	5.564	3.732	Techno Warriors Advanced
7209	6.000	5.069	3.475	6.142	Tech Hogs Robotics
6047	6.000	5.281	5.271	4.621	Twisted Axles
6022	5.500	4.987	6.605	2.612	TBD - To Be Determined
8606	5.000	5.225	5.347	4.338	RSF Intergalactic Dragons
6389	5.000	6.085	6.021	4.701	The Lazybotts
4347	5.000	5.016	5.654	3.694	NanoGurus
7477	5.000	5.224	5.673	4.160	Super 7
5202	5.000	5.515	5.049	4.974	Zip TIE Fighters
8681	5.000	4.673	5.024	4.175	A Few Loose Screws
8390	5.000	4.024	4.642	3.899	Nerd Herd
6451	5.000	4.720	4.813	4.446	Tarpon Robotics
8466	5.000	5.846	5.919	4.522	The Fellowship of the Robot
10183	5.000	2.765	2.307	4.451	KKST-Girls
10165	4.000	3.121	4.042	3.569	Apex Predators
5795	4.000	4.417	4.453	4.467	Back To The Drawing Board
5110	4.000	3.926	4.103	4.323	Wingus & Dingus
11058	4.000	4.903	4.813	4.677	AutoVortex Transilvania
9789	4.000	4.853	4.502	4.852	TOXIC
7486	4.000	3.145	4.113	3.517	Team Erebor
6220	4.000	3.068	4.335	3.190	Centripetal
9851	4.000	2.192	3.553	3.085	C4 (Computational Center…)
11059	4.000	3.513	2.752	5.270	FnC
4143	3.000	4.643	6.367	2.469	Occam's Razor

4924	3.000	3.727	3.549	4.576	Tuxedo Pandas
7591	3.000	3.783	3.797	4.473	Voltage of Imagination
4082	3.000	5.110	4.815	4.855	RoboSpartans
11057	3.000	3.151	3.071	4.808	LOG-2016
10060	3.000	4.161	4.788	3.932	Klamath Coyotes
8907	3.000	3.219	3.309	4.415	Blue Box Bots
4290	3.000	2.956	2.150	5.427	LASA High PHidelity
8686	3.000	5.219	4.323	5.367	Height Differential
8660	3.000	3.604	3.419	4.548	Charging Champions
11048	3.000	3.718	2.635	5.341	Shockwave
6109	3.000	2.707	2.702	4.008	Punabots
11042	3.000	2.792	2.619	4.172	MalFunction
7350	2.500	3.360	3.717	4.221	Watts NXT?
3415	2.000	3.073	4.545	3.029	Lancers
11052	2.000	2.162	2.278	4.324	Translate Server Error
7351	2.000	3.183	3.509	4.034	Dynamic Signals
11050	2.000	4.102	2.627	5.836	Elite Engineers
8668	2.000	2.834	3.950	3.382	Error 404: Team Name Not Found
2997	2.000	3.172	2.372	5.048	Beauty Bot and the Beasts
11051	2.000	2.148	1.606	5.481	PATTERN
11040	1.000	2.177	2.431	3.910	Return of the Screws
8913	0.000	0.919	1.062	4.254	Brainy Bots

A = expected # of wins for this team with this schedule
B = expected # of wins for this team with an average schedule
C = expected # of wins for an average team with this schedule
4.5 = expected # of wins for an average team with an average schedule

Discussion

- Again, top team Bobots had a favorable schedule.

- It is possible that the OPR for some top teams is underestimated if the teams score for their opponents late in matches to increase their Ranking Points, used as a tiebreaker in FTC. A team that can score a lot but chooses to score for their opponents will have an artificially lowered OPR and their underlying stats may actually be better than columns A and B show.

- RoboKnights 5220 had the best schedule, raising them from a solid 6.1 win team to a 7.2 win team in this tournament. RoboCats Delta and Tech Hogs were also both helped with some of the most favorable schedules.

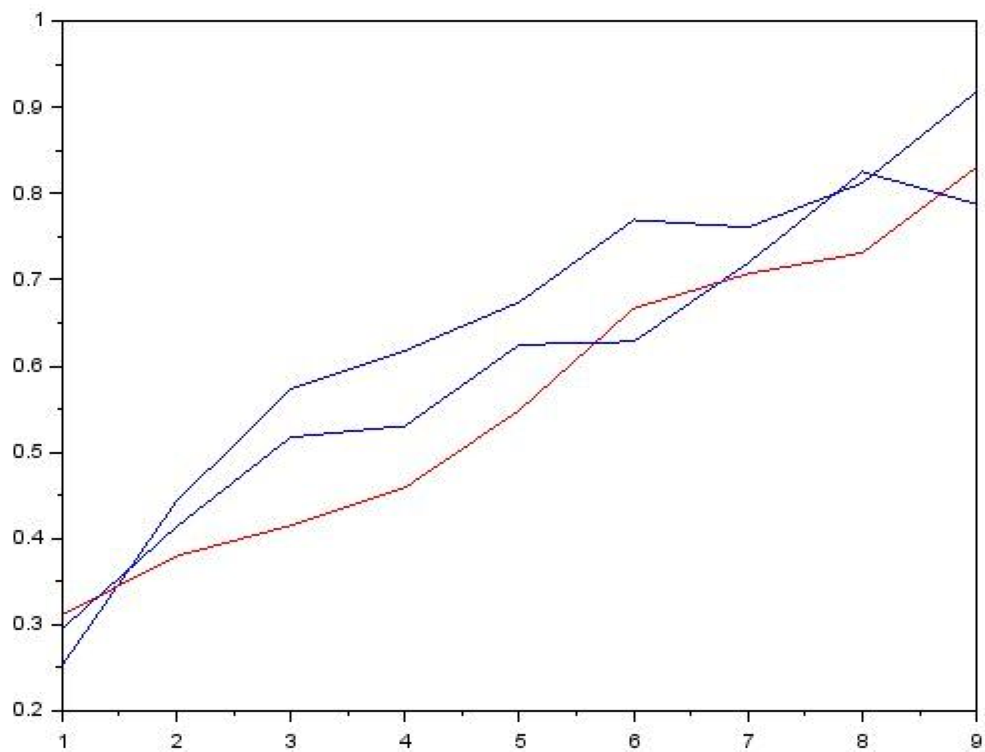
- Poor Occam's Razor! They had the worst schedule in the division, which dropped them from a 6.4 win team to a 4.6 win team! 2 Bits and a Byte, TBD, Centripetal, and Lancers were also hurt by particularly unfavorable schedules.

- In this tournament with 9 matches but 64 teams (so less ability to ensure proper cross-match play among teams), the win range for an average team ranged from 2.5 to 6.4, or nearly 4 matches due to match schedule alone!

Overall Discussion of Results

The following plot shows the standard deviation of the "C" column in the previous sections as a function of the number of matches played. The X-axis value of 9 represents the full set of qualifying matches. The X-axis value of 5 represents the standard deviation of column "C" if the tournament was stopped after only the first 5 matches.

The red line represents the 2016 Worlds Edison division. The blue lines represent the 2016 East Super Regional Hopper and Tesla divisions.



Standard Deviation of Match Schedule Effect on an Average Team vs. Number of Matches Played

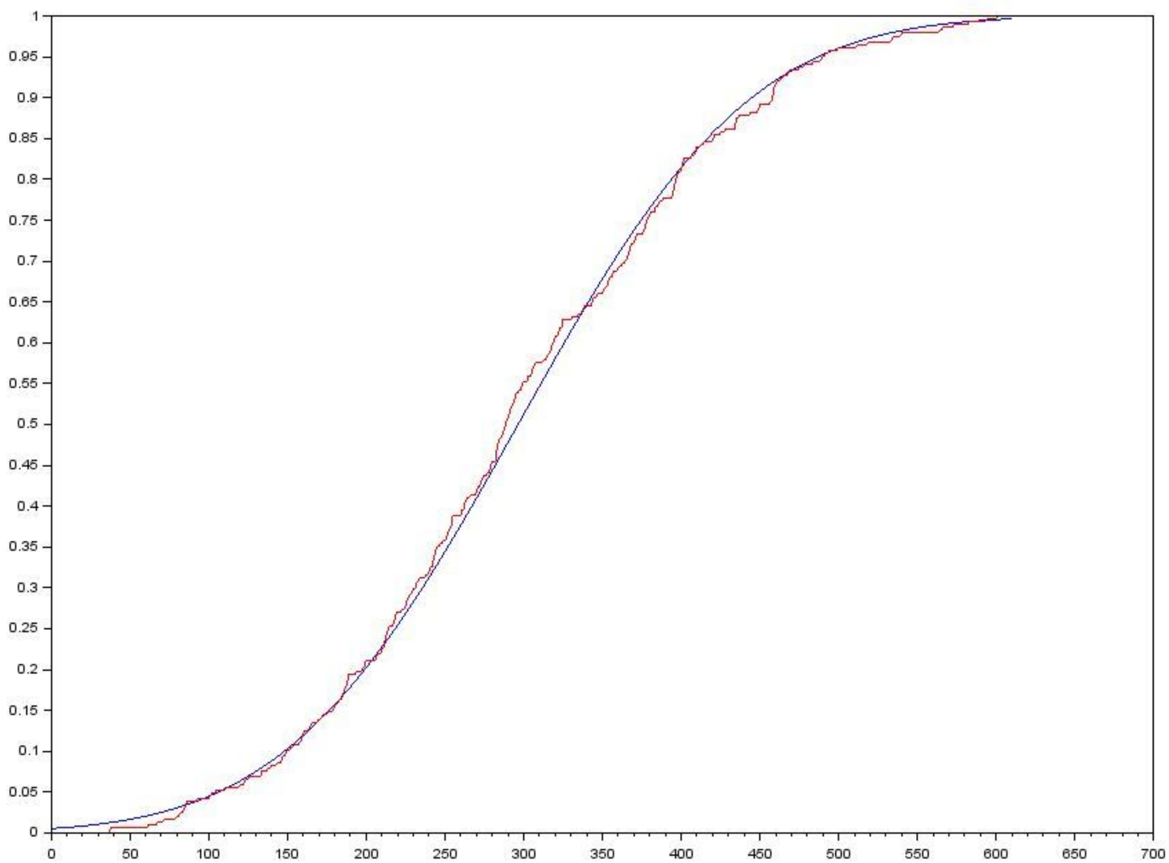
For the full 9-match qualifying tournament, the standard deviations were around 0.85, meaning that around 68% of teams had a match schedule that, if they were an average team, would affect their total number of wins by +/- 0.85 wins or less. This also means that 32% of teams had schedules that would affect the average team by more than this.

The plots are not monotonically increasing (!). It can be that a match schedule is particularly hard for the first 5 matches but then the 6th match is particularly easy, averaging out. Over many different tournaments with different match schedules and different teams, the overall average plot should be monotonically increasing.

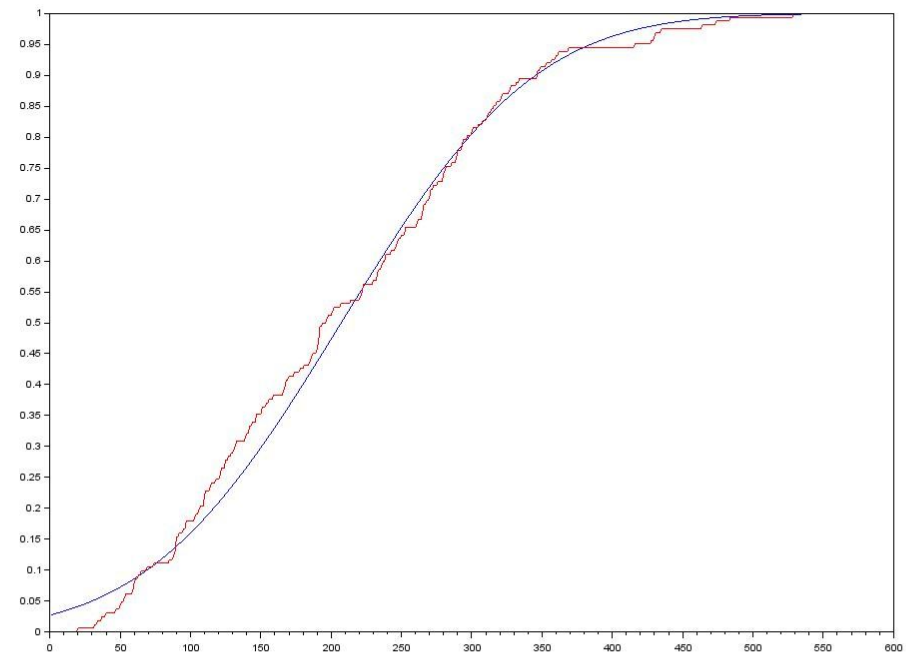
Investigating the Validity of the Model Assumptions

Comparing the distribution of the Match Scores with the Normal Distribution

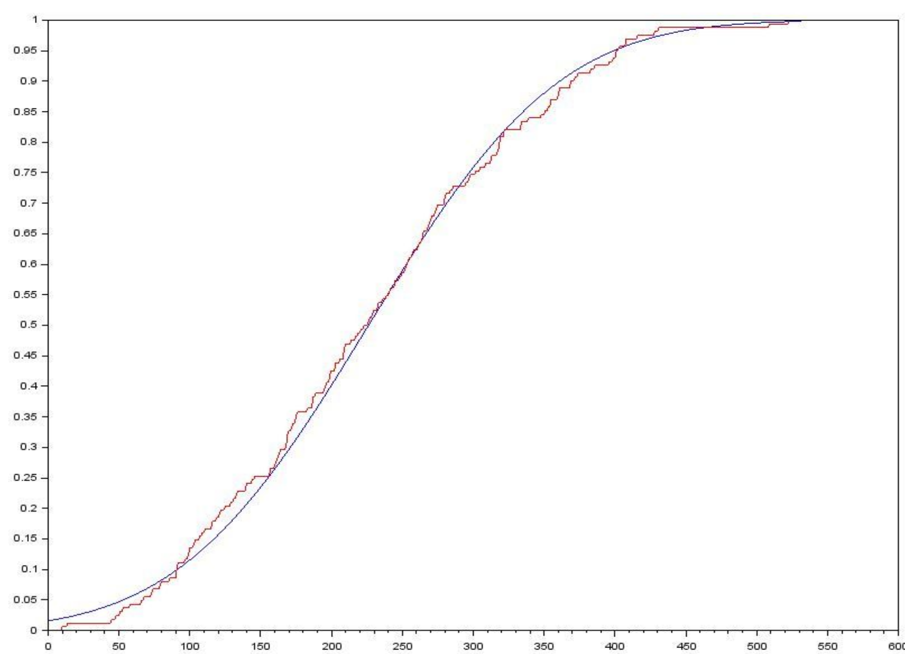
The following plots show the actual cumulative distribution for the match scores (red) and the modeled cumulative distribution (blue) with the same mean and variance as the actual data.



Match Score CDF: 2016 FTC Worlds Edison Division



Match Score CDF: 2016 FTC East Super Regional Hopper Division



Match Score CDF: 2016 FTC East Super Regional Tesla Division

Discussion

The normal distribution looks like a pretty good model for match scores. The more matches in a tournament, the better the distribution model is likely to be due to the law of large numbers. The Worlds qualifying tournament had 144 matches while the Super Regionals tournament divisions only had 81 matches, which may partially explain why the fit appears better for the Worlds plot.

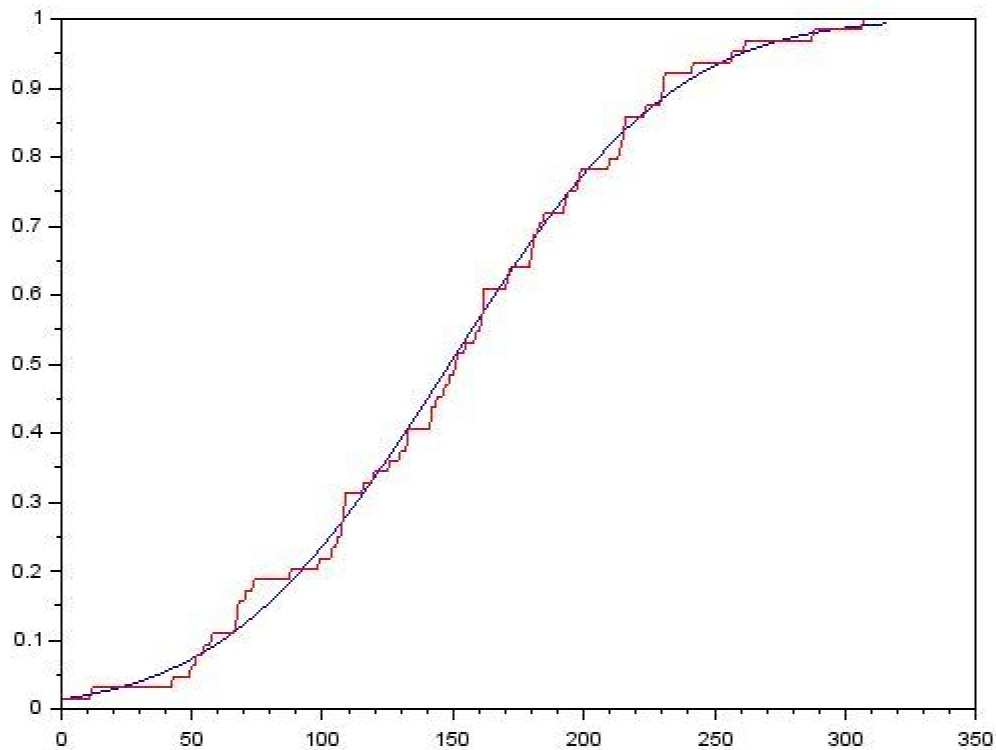
This effect may be worse in smaller qualifying tournaments with only around 24 teams and only around 30 matches total.

Surprisingly (to this author), the model CDF over-estimates how many low scoring matches there are in all three example plots. This may be the result of testing the model with some of the top tournaments (Worlds and Super Regionals). Tournaments early in the season with many robots that do not work well or at all may result in a greater number of very low match scores which may make the model less accurate for these types of tournaments.

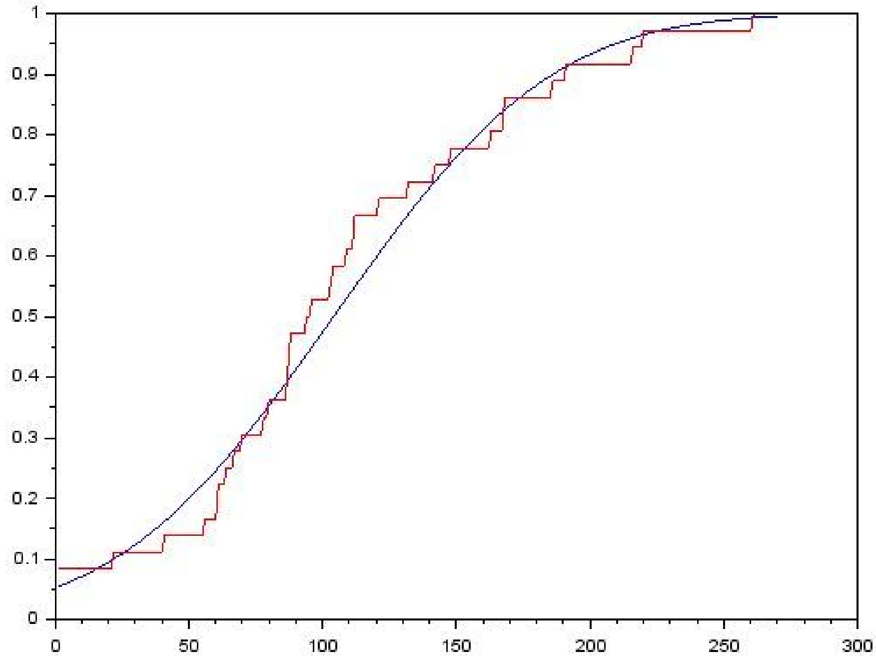
Comparing the distribution of the OPR values with the Normal Distribution

The following plots show the actual cumulative distribution for the team OPR values (red) and the modeled cumulative distribution (blue) with the same mean and variance as the actual data.

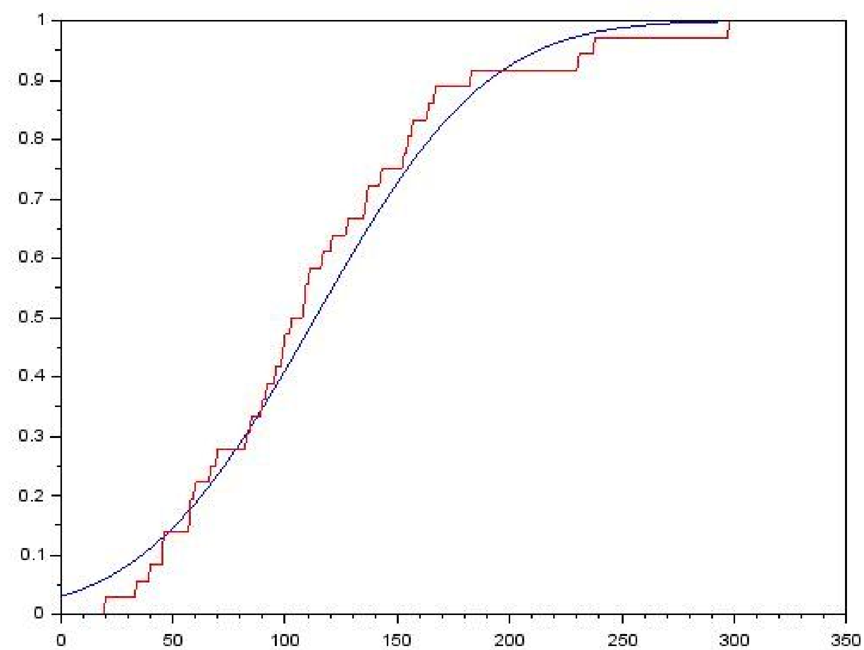
Note that there are fewer OPR values than there are match scores, so the red CDF is necessarily more “choppy” for the OPR distribution than it is for the Match Score distribution in the previous section.



OPR CDF: 2016 FTC Worlds Edison Division



OPR CDF: 2016 FTC East Super Regional Hopper Division



OPR CDF: 2016 FTC East Super Regional Tesla Division

Discussion

As with the match scores, the normal distribution looks like a pretty good model for OPR values. The more teams in a tournament, the better the distribution model is likely to be due to the law of large numbers. The Worlds qualifying tournament Edison division had 64 teams while the Super Regionals tournament divisions only had 36 teams, which may partially explain why the fit appears better for the Worlds plot.

This effect may again be worse in smaller qualifying tournaments with only around 24 teams and only around 30 matches total.

The Hopper Division had 3 teams with negative OPR values (!), which is why the red OPR CDF curve starts just below 0.1 (3/36). The OPR values were estimated using Least Squares methods. MMSE methods usually result in OPRs which are slightly less distributed at the tails.

One team in the Worlds Edison division also had a negative OPR.