“Two Subsystems of Eleven Elements”: System Dynamics and Other Approaches in Modeling Association Football

Chester S. Labedz, Jr.*
Robert P. Schumaker
A. Tomasz Jarmoszko*
David Freeman*
* Central Connecticut State University

ABSTRACT

This research unpacks the title’s quoted characterization of association football, made by an early student of cybernetics who became a legendary soccer manager. It identifies four nested domains of football activity that guide each action during a match and specifies the characteristics, abilities, activities and other elements within each domain. It provides examples of those domains’ causal interplay. Methodologically, it explores the contributions to understanding competitive match actions and results that systems thinking, system dynamics, agent based modeling, spatio-temporal modeling and dynamic network analysis offer. It proposes a model of competitive double loop learning to explain individual and team adjustments to match developments. It concludes that a multi-method approach is required to model competition among the two sport subsystems, in which system dynamics will play a limited role.

KEY WORDS

Sport modeling
Competition between subsystems
Competitive agents’ systems behavior
Multi-method modeling
Competitive double-loop learning

“Two Subsystems of Eleven Elements”: System Dynamics and Other Approaches in Modeling Association Football

Introduction and Motivation

The studies of systems thinking and soccer first intersected in the Soviet Union in the analysis of Valeriy Lobanovskyi, fabled manager of FC Dynamo Kyiv and several other teams from 1970 to 2002. His engineering training at the Kyivan Polytechnic Institute caused him to see soccer

> as a game of twenty-two elements – two subsystems of eleven elements – moving within a defined area (the field) and subject to a series of restrictions (the laws of the game). If the two subsystems were equal, the outcome would be a draw. If one was stronger, it would win. [Lobanovskyi observed that] the efficiency of the subsystem is greater than the sum of the [players’ efficiencies, which] meant that soccer was right for the application of cutting-edge cybernetic techniques being taught at the institute. Soccer, he concluded, was less about individuals than about coalitions and the connections among them. (Wilson, 2013: 279)

Association football (known as soccer in the United States) is a ball sport contested on a rectangular field of play or “pitch” by two competing teams, generally of eleven active players each, according to seventeen “laws” of the sport (FIFA, 2014), officiated by a referee and several assistants. A match is at least ninety minutes long. During it, each team or “side” usually aims to score goals greater than or at least equal in number to the goals it concedes to the opposing team. A goal is scored by propelling the soccer ball mostly by players’ feet and heads into a rectangular goal, measuring 8 feet high by 8 yards wide, that is centered at their opponent’s end of the field. Soccer is played and followed throughout the world more than most any sport, and is known as The Simplest Game (Gardner, 1996). Modeling play throughout a match however is anything but simple. This paper initiates research to frame a computational model for understanding the complexity of the simplest game.

Simulation in soccer

Simulation of association football matches in any form of computing environment dates back to arcade games in the 1970s (Kohler, 2005) and to the annual RoboCup international robotics competition founded in 1997. The name RoboCup is a contraction of the competition's full name, "Robot Soccer World Cup”. (Wikipedia, 2015) The sponsoring RoboCup Federation aims “to promote robotics and [artificial intelligence or “AI”] research by offering a publicly appealing but formidable challenge, [namely that] a team of fully autonomous humanoid robot soccer players shall [by 2050] win a soccer game, complying with the official rules of FIFA, against the winner of the most recent World Cup." (RoboCup Federation, 2015)

Weise (2006) lists some of the challenges facing AI/robotics researchers in pursuing their objective, giving the complexity of heading the ball successfully into the goal as a prime example. The competition has promoted substantial research effort. RoboCup Symposium papers have appeared for more than a decade as Springer Lecture Notes on Artificial Intelligence.

Soccer simulation research extends beyond the RoboCup competition. Ahmadi, Lamjiri, Nevisi, Habibi, and Badie (2003) make two proposals intended to cause simulated player-agent behaviors to better imitate real-life soccer competition. They propose a two-layered case-based reasoning paradigm that estimates optimal formats of case-based modules, thereby greatly reducing the number of cases that the simulation must store. Then, through continuous interaction between the data-gathering layer (players) and data storage and analysis (manager), leadership prescribes players' activities and uses the data that they collect to enhance future predictions and instructions. In the process new cases are obtained and prior stored cases are revised.

Van der Kamp (2006) tested for effects on successful penalty kick placement in a simulation in which groups of individuals received varied instructions on their shot-taking strategies and varied information regarding goalkeeper movement during their shots. Tuong Manh Vu, Siebers, and Wagner (2013) also simulated penalty kick-taking. They observed that use of crisp sets (Ladeh, 1965) within a belief-desire-intention software model can lead to unwanted "preferred" actions, due to sudden variation among ranges of decision variables, while fuzzy set use led to smoother transitions and more consistent decisions. Bazmara (2014) focused on desired characteristics of football players based on position played. They offer a fuzzy set based model called "soccer player position identification" to identify the most appropriate position for each.

FIFA15 (2014) and its forebears are a popular association football simulation video game developed by EA Canada which runs across a variety of gaming and personal computing platforms. In both association and American football, increasingly "realistic" video game simulations project match outcomes and function as learning laboratories (Sullentrop, 2015).

In articulating relationships and simulating behavior within real-life soccer matches, several overlapping or at least complementary perspectives and methodologies come to mind. We present these next.

Modeling approaches: systems, agents, space/time, social networks

Lobanovskyi's characterization of soccer, quoted above, speaks of systems, elements and area. This may be read to suggest that three complementary methods, corresponding to those components, be used in framing a computational model of association football. As we explain below, we believe that a reasonably comprehensive model will require the use of agent-based modeling ("ABM") and spatio-temporal modeling ("STM"), at the least. We believe there will be instances in modeling agent performance in which a systems thinking or system dynamics ("SD") approach will be helpful, too. Parunak, Savit, and

Riolo (1998:1) state that SD and ABM are distinct but complementary methodologies. Macal (2010) indicates that many systems can be equivalently modeled in these two approaches, even though they "take fundamentally different perspectives when modeling a system". Because both approaches explain dynamic, nonlinear social behavior, albeit from different directions, Rahmandad and Sterman (2004) and others have called for cross-study and joint research between them.

Systems theory and systems thinking

Systems theory, first advanced by Ludwig von Bertalanffy (1945, 1968), plus the early cybernetics work of Norbert Wiener (1948, 2013) and Ross Ashby (1956) provide the context for Lobanovskyi's characterization of football. Both systems theory and cybernetics explore the structures, constraints, and possibilities of self-regulated systems, whether these are animal, mechanical or social.

Peter Senge's popularizing work (1990, 2006) exposed the general public to the possibilities and implications of systems thinking ("ST"). Senge (2006: 78) describes ST as a "framework for seeing interrelationships rather than things, for seeing patterns of change rather than static 'snapshots'", and for seeing interconnectedness or "feedback" among model elements. From this, Senge infers that "[t]he real leverage in most management situations lies in understanding dynamic complexity, not detail complexity". The essence of ST "lies in a shift of mind … seeing processes of change rather than snapshots" (81-2). Its "building blocks" are reinforcing and balancing feedback loops, in which effects become causes, and feedback delays, which are "interruptions in the flow of influence which make the consequences of actions occur gradually" (87).

System dynamics

Forrester (1961) extended engineering control theory to offer SD as a method to mathematically model behavior in systems. While causal loop drawings are a key tool in both ST and SD, system dynamics provides a mathematical modeling approach that extends ST through identification and specification of stocks and flows. These are key elements that employ calculus to simulate systems' behaviors. Stocks are state variables that mathematically are integrals, while flows are their rates of change (i.e., first derivatives). Stocks can represent a range of state variables from physical quantities to psychological states. Most commonly, SD models quantify flows as percentage rates of change of the stocks they affect and thereby generate nonlinear behavior in those stocks.

SD models generally treat groups of individuals (e.g., teammates) as being fundamentally homogeneous or "continuously divisible", mixed within a stock that includes all of them (Sterman, 2000). Yet players are multi-dimensionally complex and heterogeneously distinct, leading to variance within each of a number of dimensions, variance that likely will be difficult to trace in SD. Schwaninger and Ríos (2008) observe that SD does not provide a framework for pattern-based organizational structures.

In practice, firm-level consequences can emerge from individual effects in ways that evade SD modeling practices. Salient individual characteristics, and their combinations, do not always follow normal distributions across populations. To try to account for such heterogeneity in data sets, SD software permits the tracing of aging chains and simultaneous co-flows, as well as the use of data subscripts. Repeated use of these techniques quickly becomes cumbersome, however, as the number of dimensions of interest grows, as Cavaleri, Labedz and Stalker (2012) demonstrate. Macal and North (2010) describe ABM as a way to model the dynamics of complex adaptive systems that often self-organize themselves and create emergent order, and we turn next to that approach.

Agent based models

In actual play, each team's players form a dynamically positioned network of eleven agents who follow individual and collective decision rules to the best of their personal abilities, and in response to opponents' actions, within their team's broader tactical "game plan". They interact with their teammates, opponents, and other elements of the environment. Their individual behaviors arise as they and others employ decision rules (Holland, 1995). Kirman (1992) argues that reducing characteristics of such agents to one of uniform sameness is usually unjustified and causes misleading conclusions.

Researchers employ agent based modeling ("ABM") and complex network mapping to model complex adaptive systems (Holland 1992, 2006); we focus on the former here. In modeling systems consisting of active agents, Borshchev and Filippov (2004) argue that ABM is more efficient than other techniques. It focuses more, and more efficiently, than does SD on individuals' interactions, modeling and examining the "global consequences of [their] individual or local interactions…" (Scholl, 2001). ABM has been used to simulate several personnel issues outside football, including the hiring process and cessation of employment (Tesfatsion, 2001), organizational withdrawal behavior by employees (Hanisch, 2000), and motivational effects of pay for performance systems (Schwab and Olson, 2000).

Several scholars have combined agent-based and system dynamics models. Größler, Stotz and Schieritz (2004) designed a small Vensim model to provide internal decision-making schemata to supply chain agents modeled using the RePast agent software. Akkermans' SD model incorporated supplier and customer agents who differed only in "the degree in which they emphasize the short-term or the long-term performance of their counterparts…" in making contracting decisions (Akkermans, 2001:4). Geerlings, Verbraeck, de Groot and Damen (2001) modeled the manpower planning process in the Royal Netherlands Navy. Labedz and Stalker (2008) described challenges and responses in designing and implementing a multi-level SD model for anticipating employee retirements that accepted periodic agent-level data overrides.

Spatio-temporal modeling

Gudmundsson and Wolle (2014) note that several firms currently offer the ability to track visually the locations of soccer players and the ball with high accuracy and resolution, then offer tools (relating to passing, pass sequencing and player trajectories) to aid the task of automated football data analysis.

Lucey, Oliver, Carr, Roth and Matthews (2013) note the greatly increased volume of ball and player tracking information generated within professional sports for analytical purposes but its limited utility to date in analyzing a team's tactics and strategy. They provide an overview of the types of analysis currently performed mostly with hand-labeled event data and highlight the problems associated with the influx of spatiotemporal data. They test their approach through analysis of nearly 380 matches. In doing so, they represented team behavior by chunking the incoming spatiotemporal signal into a series of quantized bins, and generate an expectation model based on a codebook of past performances.

Wei, Sha, Lucey, Morgan and Sridharan (2014) also observe teams' increased and unmet interest in using spatiotemporal data for competitive advantage. They identify as obstacles a lack of a suitable ordering of players that can be immune to the extremely large number of possible permutations, and the high dimensionality of the temporal signal. They use "role-representation" technique as well as a feature reduction strategy to form a compact spatiotemporal representation, to determine likely team formation patterns.

Bialkowski, Lucey, Carr, Yue, Sridharan, and Matthews (2015) also note that the collection of player and ball tracking data is fast becoming the norm in professional sports, [but that] large-scale mining of such spatiotemporal data has yet to surface. They use minimum entropy data partitioning to align multi-player tracking data, allowing for the visualization of formations and providing grounded role-based information on individual players. They test their approach using data from nearly 380 professional matches (approximately 480 million data points, as collected ten times per second) and present a method for identifying teams' formations from role distributions.

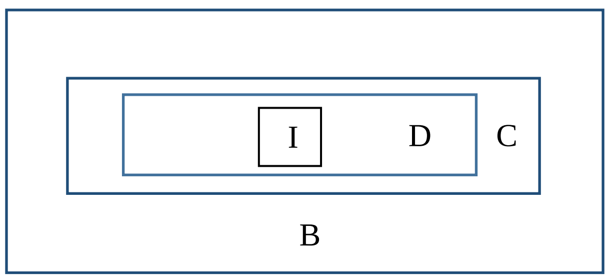
Social network modeling

Recalling Lobanovskyi's depiction of a football contest between subsystems of eleven elements, we may see players and their opponents as elements of two interlocking social networks that compete for match success. Much social network research to date depicts groupings at discrete points in time. Published research regarding so-called dynamic networks (Carley, 2003) and tools for studying these trails other approaches that we review here, but this emergent field may in the future help to understand soccer and other organizational success (Jenewein, Kochanek, Heidbrink and Schimmelpfenning. (2014); Lee and Lee (2015)).

Which approach or combination of approaches is most likely effective in modeling the behaviors and performance within the football subsystems that Lobanovskyi observed? What role should SD modeling play? To lay a foundation for answering this question, we turn now to a framing of relevant characteristics, abilities and spatial considerations that footballers face, and behaviors they enact.

The domains of football activity

Each player's actions throughout a match (what he "Does") relate to four domains. First and centrally, data on who he "Is" consists of certain physical characteristics (height, weight) and capabilities (stamina, jumping and running abilities), personal motivation, and current position on the pitch. Second, the set of all activities he is then able to perform comprise the set that he "Can" do at a particular moment t_n. Third, because at any t_n he can only perform those activities of which he is then capable, "Does" must be a proper subset of "Can" activities. Why he chooses at each t_n to act as he does, from among the set of all activities he is then able to perform, largely is bounded and governed by the "Because" of teammates, opponents, team expectations, planned tactics, encountered tactics, match conditions, pitch position, the ball's location, and the like. Thus for each player on the field, as well as substitute players poised to enter from the sideline, the four domains nest as shown in Figure 1.



I =Is; D = Does; C = Can; and B = Because.

Figure 1. Diagram of nested IDCB domains

The player's makeup: the "Is" domain.

Data elements of this domain include some that do not vary within a match (the player's height, team affiliation), others that vary somewhat predictably (weight, stamina), and some that are more situationally dependent (e.g., position on pitch). Within a player's "Is" domain we also include elements of his background, experience, skills and knowledge going into the match at hand. Labedz and Berry (2011) frame an individual's entire set of work-related characteristics, skills and knowledge, and motivations, and environmental factors, within a Right WorkForce™ model.

Each player brings to a match a set of personal characteristics, abilities and motivations: the essence of who one "Is" as a player. These qualities affect his success in translating each action choice ("Can") into a "Does" accomplishment. In fact, his understanding of his "Is" qualities (and other factors) often will influence his "Can" choice. In short, he may select one action (of which he is more capable) over another of which he is less sure.

For example, taller players may be more successful in heading the ball, and quicker players may fare especially well in accomplishing a maneuver known as "beating the offside trap". A confident player who values individual achievement may choose to take on a defender by personally dribbling the ball rather than passing it to a less-defended teammate. Knowledgeable defenders may successfully "escort" an opponent who strongly favors one foot over the other into less threatening attacking opportunities on the opponent's "weaker" foot.

Table 1 sets forth the individual characteristics, abilities and range of motivations – "who" one "Is" as a player included in a club or national team roster – that affect his success in translating his action ("Can") choice into a "Does" accomplishment.

Table 1. Principal elements of the field player's "Is" domain

Characteristics	**Abilities**	**Motivation**
1. height 2. weight 3. center of gravity 4. preference for foot 5. incidence of injury 6. impediment by injury 7. physical conditioning 8. stamina 9. nationality / ethnicity 10. gender 11. pitch location	12. heading effectiveness, 13. right- or left-footed: a. dribbling, b. passing, c. shooting power d. shooting accuracy 14. tackling ability 15. ability to "see the field" 16. sprinting ability 17. quickness 18. ability to find "open space" 19. ability to advance and cross the ball and others as valued by specific clubs.	Drives: 20. for individual performance excellence, 21. for personal recognition, honors, 22. for team success, 23. for team harmony, 24. to improve or maintain contract status (at a cost to team in future years), and 25. to maintain one's roster and lineup positions, or corresponding forces promoting demotivation.

Data elements of the "Can" and "Does" domains

Team possession of the ball changes often in the course of a professional soccer match, as in several other sports. Anderson and Sally (2013: 112) estimate that each team turns the ball over to its opponent nearly 200 times per match, and that teams "control" possession – retain it for more than a fleeting moment – in only about half of those cases. Whenever one's team possesses the ball, we call all of its members "attackers", whether each personally is then actively pursuing an attack or not. At that same instant, all one's opponents are "defenders". With almost 400 turnovers on average per game, attackers become defenders, and vice versa, every fourteen seconds on average. Anderson and

Sally conclude that [s]occer is not a possession sport. It is a game of managing constant turnovers."

Against that landscape of oft-changing possession and roles, we enumerate possible and actual player activities, the "Can" and "Do" domains, within three player statuses. We focus first on the single player who is currently in possession of the ball, then on his teammates, who are all temporarily "on attack", and then on their opponents, each temporarily "on defense". (We postpone consideration of goalkeepers, who rarely take on an attacking role or even venture more than 24 meters from the goals they defend, to later research.)

Possible Actions of the Player in Possession

A player with the ball faces an immediate fundamental choice: to try to retain it personally, or not. This player often must make the choice under time pressure due to an immediate or impending challenge from an opponent, an emerging or disappearing opportunity to shoot or to pass the ball to a teammate, or (least often) a time limit imposed by the sport's laws. The player in possession ("PIP") often does not possess perfect information about the likely consequences of each action available to him. With each time he chooses to try to retain possession personally and succeeds, he confronts a next multimodal choice within moments. So do many of his teammates and members of the opposing team, all as described in subsequent sections.

Empirically, a PIP's action in trying to <u>Control the ball</u> personally involves retaining possession through one of three tactics. He may try simply to hold possession of the ball at his feet, awaiting a later moment at which to take other action. (Often he shields the ball with his back to his opponent as he tries to "hold" or retain personal possession.) Alternately, he may attempt to dribble the ball deftly around or through his opponent's feet while maintaining close contact with it. Third, he may pass the ball to himself "in space", striking it past his opponent and then retrieving it before anyone else can do so.

A PIP who chooses not to try to retain it personally generally tries to <u>Pass</u> it to a teammate (or to anywhere else on the pitch that seems safer, at that time, for his team's fortunes) or to <u>Shoot</u> it at the opponent's goal. (In extreme circumstances, the PIP <u>Gives Up</u> possession by sending the ball into an empty space on the field, or to a distant opponent, or even out of bounds.) Occasionally, he may risk <u>committing a Foul</u> (a violation of the laws) to advantage his team. Although he may be said to operate "by instinct" at points in time, the PIP presumably makes a simplified optimizing decision with each touch of the ball. He seeks the best (or least bad) estimated Outcome for his team among these choices: attempt to Control the ball personally, Pass it, Shoot it at goal, Give up possession, or commit a Foul. His optimizing algorithm is MAX @ t_n (O_C, O_P, O_S, O_G, O_F). Often, multiple teammates present him (e.g., O_{P7}, O_{P10}) passing opportunities at t_n, sub-options for him within O_P.

What is that next Outcome for his team? Customarily the favorable ones are that his team continues in possession or it scores a goal. An unfavorable Outcome usually means neither continued possession nor goal scored. Possession here means his continued possession of the ball, its possession by a teammate, or possession awarded to his team by a law (as in sideline throw-in, a free kick awarded upon an opponent's infraction of the laws, or a corner kick). Yet some teams have succeeded over the past century without high quantity of possession (measured in percentage of minutes per match) or frequency of shooting or goal scoring. Those successes suggest an additional success criterion or refinement, Quality of Possession, which we will explore below once we define the basics of play while <u>not</u> in possession.

Activities of PIP's teammates

What activities do a possessing team's players pursue when they personally are not in possession of the ball? Those activities mostly involve each individual's positioning on the pitch. He may try to <u>Improve</u> his position to receive a pass, thereby offering a greater passing O_P to the PIP. He may instead take little or <u>No action</u>, as when he is appropriately positioned at that time to play his defending role if his team loses possession. In <u>Attacker covering</u>, he moves to cover a defensive assignment that an attacking teammate will not be able to perform if their team loses possession. In some cases, as in "selling a dummy", an attacking player's best option may be temporarily to <u>Refrain</u> from touching the ball or being involved in play at all. Or, like a PIP, he may need to risk <u>committing a Foul</u> to advantage his team. In summary, attackers when not personally in possession are making and remaking choices often from among this set of possible activities, each striving for optimal consequences for their team: [I, N, A, R, F].

Activities of PIP's opponents

Each player on the non-possessing team always engages in one of eight activities: Challenging, Escorting, Marking, Blocking, Defending, Trapping, Refraining, or Fouling. By <u>Challenging</u> *("X")* we mean actively challenging the PIP for possession of the ball. In <u>Escorting</u>, a defender instead simply tries to force the PIP to follow a path the attacker does not prefer; examples include forcing the PIP to play the ball with his "wrong foot" or to play too close to a boundary line. By <u>Marking</u> we mean paying defensive attention to an opponent who is not then in possession. <u>Blocking</u> refers to a defender's success in impeding an opponent's intended pass or shot, wherever that impairment may occur along the ball's path. In <u>Defending</u> ("Z") we mean otherwise positioning oneself properly to defend, including moving to cover a defensive assignment that a teammate appears not able to perform, as when a teammate has "lost" his defensive assignment.

<u>Trapping</u> refers to a specific maneuver, countenanced by the laws, in which defensive players act to gain ball possession – by <u>not</u> actively defending. Such an "offside trap" is orchestrated by defenders who move away from their own goal line in unison so as to position a pass-receiving attacking player closer to it than they are, at the moment his teammate (passer) strikes the pass. If the offside trap succeeds, the referee stops the attack and the attacking team loses possession of the ball. If the maneuver is unsuccessful, however, an attacker may "spring the offside trap" and possess a particularly attractive opportunity to shoot and score a goal.

In some circumstances, Refraining as defined previously may be an appropriate choice for a defender too. Most Fouling occurs when a defender challenges or blocks an opponent or a shot, but – despite its resulting penalty – a defender’s commission of a foul may be an outcome preferred by his team. Thus, defenders constantly are making and remaking optimizing decisions from among this set of eight activities [X, E, M, B, Z, R, T, F], a set larger than the one available to attackers.

Table 2 compiles the set of the actions from which players choose at any given match moment. In normal circumstances, there are one PIP, nine other attackers, and ten defenders on the pitch, plus each team’s goalkeeper. What each of the field players attempts to do in the moment is his single choice selected from the multiple options then available to him. As in Figure 1, “Does” is thus a proper subset of “Can”. A player’s chosen action also depends for selection and success upon his “Is” and “Because” domains.

Table 2. Possible “Can”/”Does” activities of non-goalkeeping players at each t_n.

Player in possession	Other Attackers	Defenders
C: control the ball personally, holding, dribbling or self-passing it		X: challenge the player in possession for the ball
		E: “escort” the player in possession on a path he does not prefer
P: attempt to pass the ball to a teammate	I: improve one’s position to receive a pass, by traveling to another location	M: “mark”, or pay defensive attention to an attacker who is not in possession
S: attempt to shoot the ball at the opponent’s goal	N: take no activity, believing oneself properly positioned	B: attempt to block an opponent’s pass or shot
	A: on attack, position oneself to “cover” defensively for a teammate’s positioning	Z: on defense, otherwise position oneself “properly”, including to “cover” for a teammate’s positioning
	R: when to his team’s advantage, refrain from touching the nearby ball	R: when to his team’s advantage, refrain from touching the nearby ball
G: act to give up possession, as in clearing the ball “into space” or across a boundary line		T: attempt to trap an opponent in an offside position
F: commit a foul	F: commit a foul	F: commit a foul
Optimizing algorithm: MAX @ t_n (O_C, O_P, O_S, O_G, O_F)	Optimizing algorithm: MAX @ t_n (O_I, O_N, O_A, O_R, O_F)	Optimizing algorithm: MAX @ t_n (O_X, O_E, O_M, O_B, O_Z, O_R, O_T, O_F)

Data elements of the "Because" domain

The "Because" domain includes all relevant environmental factors external to the individual player. Within that domain, we identify teammates, opponents, team leadership, team objectives and expectations, team formations, planned tactics, encountered tactics, match conditions, match developments, and the like. It also includes player and ball positioning on the pitch throughout the match, a topic covered in a separate section below.

Thus, the "Is", "Can" and "Does" aspects of each teammate and opposing player constitute important elements of a player's environment, and his of theirs. Each player, with his characteristics, attributes and continual choices among individual activities, is one of the twenty-two elements that Lobanovskyi discerned in the competing subsystems.

A team's formal (manager) and on-field (team captain, goalkeeper) leadership will shape its pre-match and within-match efforts. A host of pre-match factors will shape first expectations for a match. Thus, sometimes a team will not actively play to win, because of a greater perceived risk of loss. Instead, it will aim for a drawn result or even for a loss in which it keeps its opponent's goal total low. Yet an in-match development, for example an unexpected goal, injury, or rules application may alter such plans and expectations (and resulting team composition, formations and tactics) on the fly.

Initial and emergent team formations and tactics flow from its environmental factors. Throughout a match, tactical plans provide general positional guidance to both attacking and defending formations and individual roles. Gardner (1996) and Wilson (2013) well describe and depict the evolution of soccer formations worldwide since 1866. Wilson traces the near-inversion of soccer formations over the past century. In earliest times, teams deployed as many as five forwards and as few as two defenders. By the 2014 FIFA World Cup tournament in Brazil, managers named only one forward as a starter in seventy-nine of 128 matches.

Managers, fans, scholars and other analysts traditionally describe soccer's tactical formations through sets of three to five ordered numerals. The first value in a triad counts a team's defenders, the middle value its midfielders, and the last value the number of forwards it deploys during a given time interval in a match. When more than three values appear, the team has positioned players intermediate between defenders and midfielders or between midfielders and forwards.

The ordered arrays of tactical formations, on the part of one's team and one's opponent, reflect their managers' thinking with respect to a broad range of "Because" domain considerations that we list in Table 3. We present here two examples, not an exhaustive list, of considerations facing managers, drawn from the 2014 FIFA World Cup. In the first, hot and humid climate conditions challenged four teams' stamina and affected player substitutions in matches played at Manaus in the Amazon jungle. In the second, some managers knew, in the third match they played, that a drawn match, or even a one-goal loss, would advance their teams into the next round of the tournament. Thus

Germany and the United States knew that a draw in their match 45 would send both through to the second round of the tournament, and that even a tightly-contested loss would be enough, so long as their trailing group-mates (Portugal and Ghana) simultaneously played a tight match (FIFA match 45, 2014).

Managers coped throughout the tourney with problems in the "Is" domains of their own players and exploited such issues in their opponents. Thus, Brazil lost the skills of its most prolific player to injury after match 57, and Germany and the Netherlands routed the host nation in subsequent matches (FIFA Technical Study Group, 2014: 14, 16). In some cases, managers coped or exploited issues through their selection and modification of tactical formations. In the tournament, in half of all cases, teams positioned four defenders, two defensive midfielders, three attacking midfielders, and one striker ("4231") in front of their goalkeeper. Across the other sixty-four lineups, managers announced eleven other starting formations. The United States began each of its four matches in a different formation, while tournament champion Germany began all seven of its matches in 433. As match conditions (e.g., in-match score) warranted, managers altered their tactical choices and their on-field players and attacking and "marking" responsibilities. (Labedz, Schumaker, Jarmoszko and Freeman, 2015)

Table 3. "Because" considerations in, and results of, formulating a team's tactical strategy

Considerations		**Results**
1. match location 2. match playing conditions 3. perceived strengths and weaknesses of opponent's players 4. perceived strengths and weaknesses of opponent team 5. opponents' historical tactical strategies 6. plausible desired outcome of match 7. minimum acceptable outcome of match 8. emerging patterns of match play 9. emerging score line of matches	10. match availability of own players, 11. "Is" domain elements (Table 1) of each of own players 12. comparative historical results of own players versus opponents 13. other historical performances of own players 14. perception of teams' comparative match readiness, motivation and others as identified by specific clubs,	15. opening tactical alignment 16. own defensive "marking" assignments 17. own emergent tactical alignment within match 18. opponent's opening tactical alignment 19. opponent's defensive "marking" assignments 20. opponent's emergent tactical alignment within match 21. final score line of match

Data Elements of the "Because" Domain: Player Grid Positioning

Throughout a match, the locations of one's teammates and opponents influence one's own current position and likely one's next-in-time position. Relative to each individual, others' positions therefore constitute components of his "Because" domain.

As a match begins, tactical positional plans provide general guidance to both attacking and defending formations. Chapter 8 ("Tactics") of Gardner's text well describes and depicts the evolution of soccer formations between 1866 and 1994. Its eighteen figures and Gardiner's explanations of their strategic motivations, resulting player roles, characteristics and relationships, set the stage to explain those <u>positional probabilities</u>. We take one example from it, the "Swiss bolt" or *verrou* system employed in Geneva and Zurich. It provides a striking example of the interdependence of players' characteristics and abilities with their manager's tactical planning (Table 3, result 15):

> The aim of the bolt system was to create a team that would outnumber opponents in both attack and defense …. On attack, the bolt had a 3-3-4 shape … with all the players including the three-man fullback line moving well upfield. When possession of the ball was lost, all ten players retreated. The function of the four forwards was to harass their opponents, to slow down their attack [Table 2, techniques X and M], while the other six players raced back deep into their own half [Table 2, Z]…. The attacking center half now became the center back, while the former center back retreated to an ultradeep position behind everyone else. From here he could move laterally across the field, covering the other three backs and functioning as the sliding "bolt" to lock out opposing forwards [Z]. The bolt system needed disciplined, highly fit players [Table 1, characteristics 7 and 8] who could cope with a good deal of high speed running [Table 1, ability 16] , who had the skill to operate as both attackers and defenders, and who possessed a well-developed sense of positional play [Table 1, ability15]. (Gardner: 190-1)

Diagrams 5 and 6 in Gardner's chapter 8 present players' positional "homes" on the pitch when the Swiss team, using *verrou* tactics, was in possession and when it was not. Combined, they provide a positional probability map ("PPM") based on pre-match tactical planning. In figure 3, we combine and translate Gardner's two diagrams. The manager directed each field player to move regularly within his quadrilateral area of responsibility drawn on this pitch map. He would move from his defensive "station" at left (lowest x-axis value) to attack at right, and retreat from right (highest x-axis value) to left when his Swiss side lost ball possession.

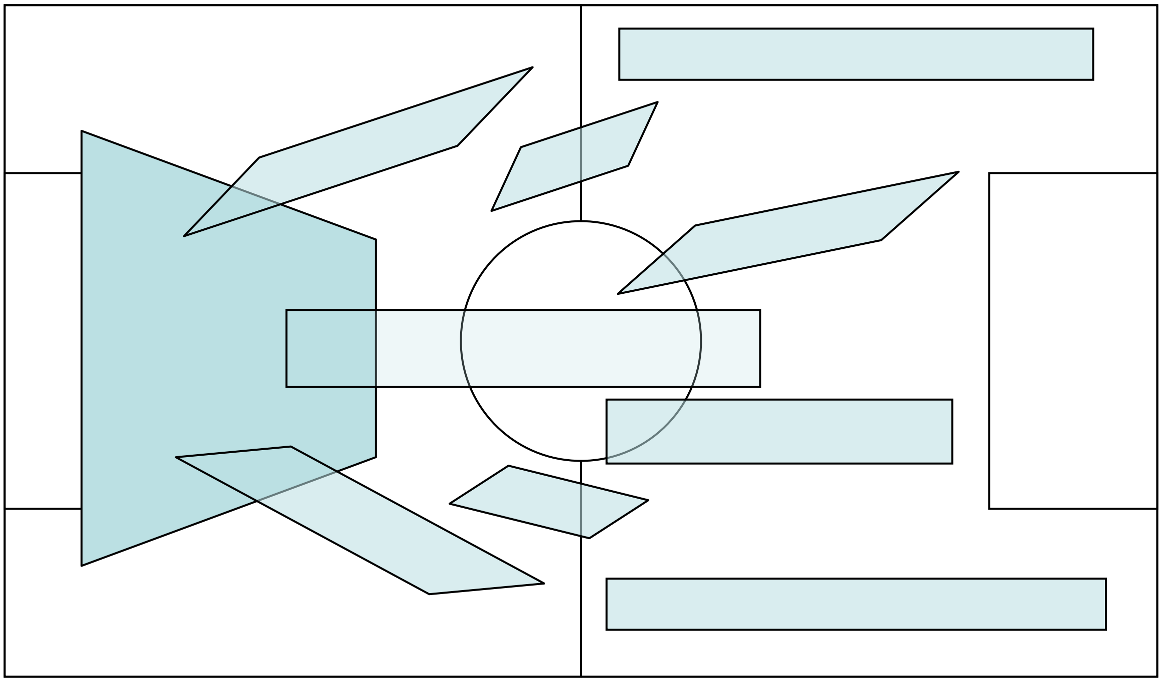


Figure 2. Positional Probability Map of *verrou* tactics

In each match moment, where does each player actually physically enact his choice among possible activities of Table 1, drawing upon his characteristics, abilities and range of motivations (Table 2), in service of his team's tactical strategy (Table 3)? Researchers and analysts have created "heat maps" out of player-by-player positional data feeds that are captured throughout each match. (Couceiro, Clemente, Martins, and Tenreiro Machado, 2014) Figure 3 displays the heat maps of the 22 starting players and substitutes during the final game of the 2014 World Cup tournament (FIFA 2014).

Even while a set of these maps displays clusters of players' positioning, they do not indicate precisely everyone's position on the pitch at any point in time. A player's heat map is an emergent (Bialkowski et al., 2015) rather than planned PPM, suggesting through a probability density function that during the match he will be found within a certain region of the pitch.

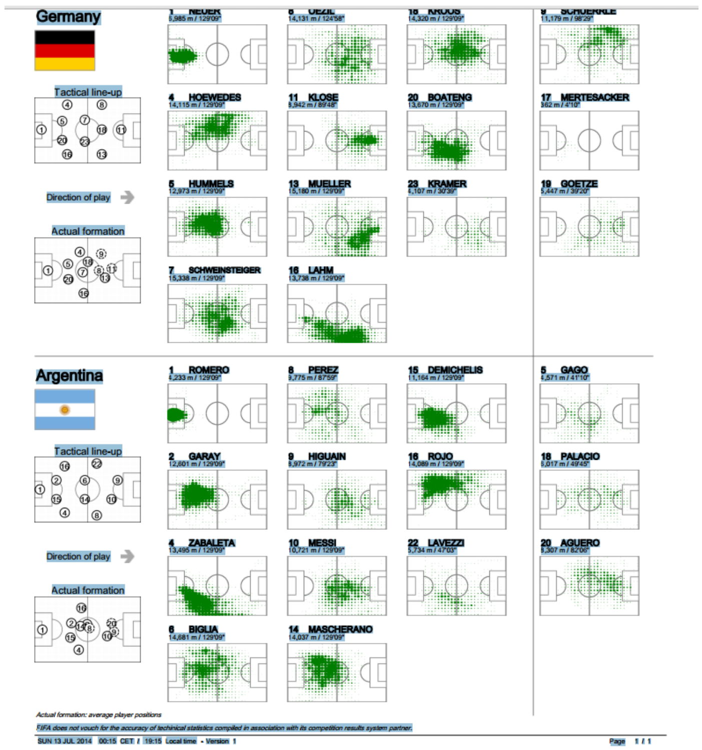


Figure 3. Heat map of FIFA World Cup 2014 championship match

Such Table 2 choices as trapping, passing "into space", improving or maintaining one's position, repositioning, challenging and marking imply the concept of positioning of attackers, defenders and the ball. All players, not merely the one then in possession, operate continuously in 4-dimensional space (x, y, z, t). So too does the object they possess. "The fastest player is the ball" said legendary coach Sepp Herberger (Anderson and Sally (2013: 107)), because its coordinates on the pitch usually change with greater speed and mathematical richness than do any player's. We explain next the 4-dimensional coordinates of the sport.

The laws stipulate a range of lengths and widths of the pitch, in metric and English units of measure. We employ here physical model boundaries of one hundred eight yards in length (x-axis) and sixty-eight (y-axis) in width, within those ranges, for convenience. While successful shots must fully enter the eight-yards-wide goals at heights less than eight feet, the relevant vertical axis for play is limited only by the strength of a player's kick and the laws of flight. The range of height in which players operate, including the maximum height at which they can play the ball while off the ground, is assumed not to exceed ten feet. While earthbound, we assume they occupy one (standing) to 2.5 (extending) square yards of turf. Thus, twenty non-goalkeeping field players occupy at any time less than one percent of the field's grassy expanse. (The regulation "size 5" soccer ball is a sphere with roughly a 22-centimeter diameter.)

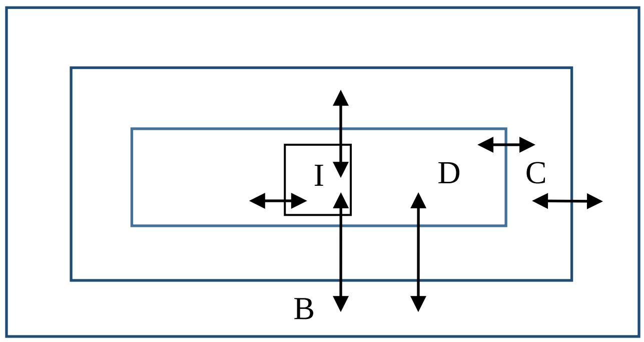
The field players likely do not occupy that same 0.75% of the pitch for long, since the play (and player movement) in soccer is more fluid than in other major team sports. What then guides their positions throughout a ninety-minute match? Inputs to their decision-making include their teams' tactical positional plans, their current locations, their capabilities and those of their teammates and opponents, emergent match circumstances, and the ever-changing position of the ball (which they also affect). So too do their forecasts of changes in those inputs in the next moment and beyond, and their memories of some of those inputs, such as opponents' tactics and positioning to date.

Using some of these inputs, the resulting dynamic optimizing algorithms of each player determine his probable position at t_n and t_{n+1}. He cannot simultaneously employ them all. A player's bounded rationality (Simon, 1957) in dealing with all those inputs must cope with physical uncertainties as well. In deciding to try to pass the ball to a teammate, he estimates his physical ability to make the pass he intends, as well as the abilities of his intended target to receive it successfully and of one or more opponents to block or intercept the pass. For example, the maker of an aerial pass presumably believes that his teammate is somewhat likely to outjump their nearby opponent and receive it successfully. In the flow of play the passer may perform this determination subconsciously and instantaneously. Weather and field conditions add to the uncertainty of the decision and its results. The ball's aerodynamics and a player's skill in striking it permit it to follow a linear or curved path intended to avoid interception by opponents not positioned along its path. The PIP's teammates and their opponents likewise play continuously within their own bounded rationality. Using a social network approach, researchers have begun analysis of passing networks in football for their effects in tournaments including the World Cup (Lee and Lee, 2015).

All this decision-making and activity take shape continuously in 4-dimensional space (x, y, z, t). We deem passes up field toward the opponent-defended end of the pitch to alter the soccer ball's x-coordinate, while "square" passes that travel parallel to the goals instead affect its y location. Most of soccer's passes and shots, and even some attempts at ball retention, lift the ball off ground level, into positive z-space. There, the height, timing and jumping ability of intended recipients and opponents affect the success or failure of the attempt. Each decision or activity occurs at a particular time. The x, y and z coordinates for each player – and for the ball – are measured as of each moment in time, t_n, but generally have changed by time t_{n+1}. Many passes and shots follow curves, the results of the ball's aerodynamics (Bush, 2013), of crudely calculated forays, practiced patterns, or intuitively shaped decisions of the passer, or by accident. The trajectories of a pass may be as simple as a linear vector that the ball traverses along the ground during a specific time interval $(x_{tn+1} - x_{tn},\ y_{tn+1} - y_{tn},\ 0,\ t_{n+1} - t_n)$. The greater computational challenge is provided by bending (Dhami, 2003; RWPP, 2015), swerving and dipping passes that follow curve segments defined in space by a trio of third-order polynomials of form $x(u) = a_x u^3 + b_x u^2 + c_x u + d_x$, where $0 \leq u \geq 1$, etc. (Mortenson, 2006)

A common defensive tactic offers an example of the importance of coordinating "probabilities" of positioning "in the moment". Success or failure in "beating the offside trap" emphasizes the relative y-coordinates of the passing PiP, his teammate-receiver and last opponent defender, but only at the instant the pass is struck. Other factors may affect the success of that pass too, such as passing and receiving skills, proximity of other defenders, and the accuracy of the offside call (laws enforcement) made by the referee's assistant.

Thus, elements of the four nested domains influence one another. Actions, reactions and conditions of the individual player and his environment affect each other throughout a match, and beyond. In Figure 4, we superimpose on Figure 1 six bidirectional arrows representing those paths of influence.



I =Is; D = Does; C = Can; B = Because. Arrows indicate reciprocal influences.

Figure 4. Diagram of influences among nested IDCB domains

Next, Table 4 offers an example of each Figure 4 vector, listed in "from → to" order.

Table 4. Examples of domains' influences on one another

Vector	Example
I → B	A tall player's preeminence draws opponents' attention to him in ball-heading situations.
B → I	Over the longer term, competitors' capabilities and physical attributes influence individual training, roster inclusion, and skills emphasis.
I → C	A player with a "weak" left foot cannot control the ball well with that foot.
C → I	A player's skills may inspire his greater pre-match confidence or motivation.
I → D	A player with a "weak" left foot insists on challenging opponents on the other.
D → I	A player's in-match successes and failures may affect his in-match motivation or confidence.
B → C	Opponents deny an opponent touches of the ball, through close marking, fouls.
C → B	A player's recent "run of form" forces countermeasures in the opponent's lineup.
B → D	Opponents "force" a weak-footed player to use that one ineffectively.
D → B	A player's in-match successes force in-match countermeasures, substitutions.
C → D	A player who is not "match fit" performs less effectively.
D → C	A player aggravates an injury during play, and thereby becomes less capable.

Application of SD and ST

Research that uses SD modeling in connection with health concentrates on improving health care delivery at the facility or system-wide level (e.g., van Olmen, Criel, Bhojani, Marchal, van Belle, Chenge, Hoerée, Pirard, Van Damme, Kegels, 2012), and not on individuals' recovery from traumatic or strain injuries. Nonetheless, medical research with respect to recovery from injury, player conditioning and "match fitness" provides rates and patterns of improvement over time. In a study of athletes' recovery from posterior thigh injuries (Malliaropoulos, Papacostas, Kiritsi, Papalada, Gougoulias and Maffulli, 2010), for example, an s-shaped growth structure depicts a pattern of full recovery of active range of motion within a 14-day period. Figure 5 presents the stock and flow structure. The underlying definitions and formulas and a graph of the model's simulated behavior appear in the Appendix.

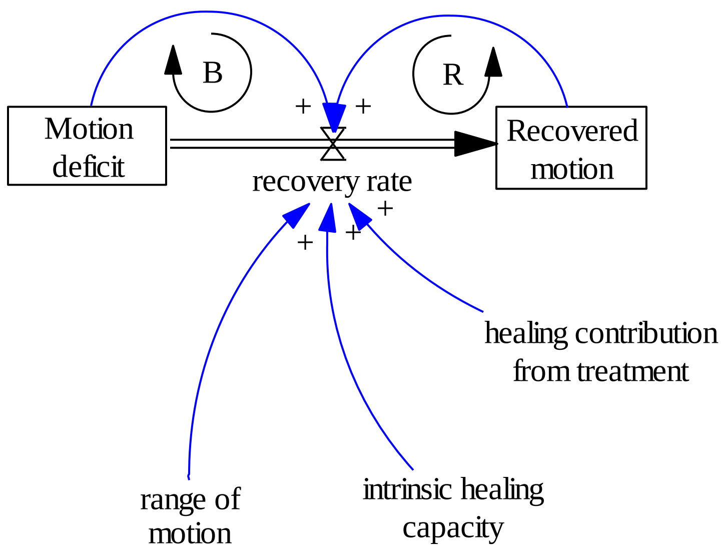


Figure 5. Stocks and flows of player recovery from soft tissue injury

With respect to player stamina levels, stock and flow structures that produce patterns of s-shaped decay or exponential decay appear most appropriate. While rates at which these variables change during a match will vary among players, their overall distribution across a population of players likely will be a normal one. Perl (2002, 2004, 2005) developed a stocks-and-flows model and tool for the analysis and optimization of athletes' load-performance interaction. Abdel-Hamid (2002) used a system dynamics model to study and gain insight into physiology related to weight gain and loss. Based on these, Figure 6 presents in-match energy level through a generic stocks and flows formulation in which capacity (response potential) and exertion (strain potential) affect stamina (performance potential) over time through the respective delays in their unequal and variable response and strain flows. It is likely that the Load Input for Response potential is based on player conditioning efforts ("I" domain, characteristics 7 and 8), while "loading S" is influenced by match conditions and developments ("B" and "D" domains).

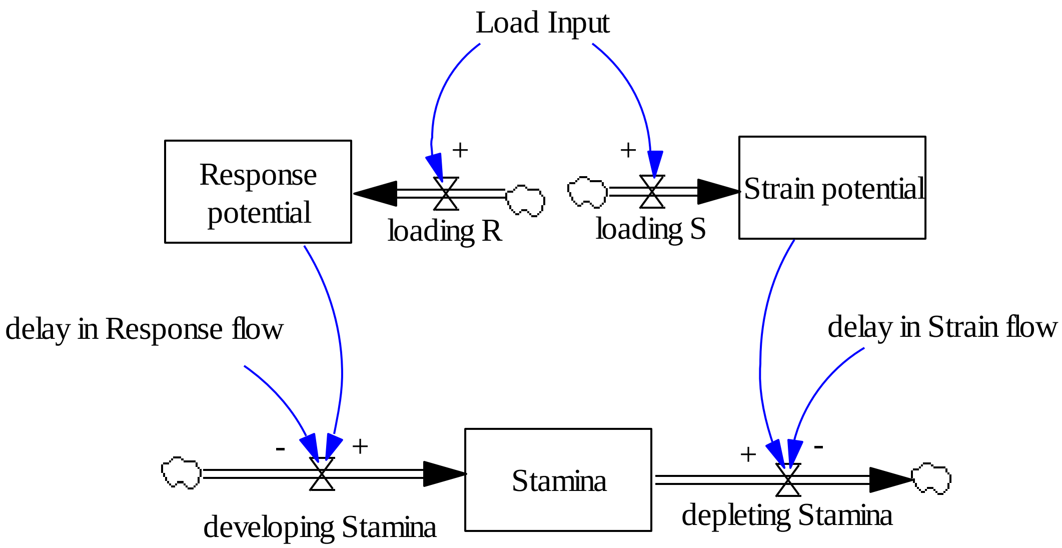


Figure 6. Stocks and flows of player stamina / energy

The greatest contribution of the SD and ST approaches likely describes players' adjustments to their opponents' tactics, successes and failures. Learning is a feedback process, and learning during competition doubly so. For example, actions taken by attacking players lead to successful or unsuccessful outcomes (from their perspectives) as defenders take countermeasures. A pattern of outcomes within the match (or even one that extends some patterns from prior matches) may cause players or their manager to reconsider their tactics. Reconsideration may lead to considering and testing revised approaches, and these revisions may lead (they hope) to more-favorable outcomes. Meanwhile, of course, opposing players and their manager may undertake similar tactical reconsideration and pursue their own revised approaches. These patterns of competitive re-thinking pit against one another two cases of double loop learning (Argyris 1985; Sterman, 2000) at group and individual levels. The expected outcomes of each side represent the intersections of their opponent's tactics, into which they enjoy lesser visibility, and their own. Managers, analysts and fans expect that delays in tactical reconsideration and adjustment by either side can affect the competitive outcomes. This combination of competing single- and double-loop activity, expectations of intended change in tactical outcomes, less-transparent insight into opponent adjustments, and effects of responsive delays, lead to a more complicated model of double loop learning. Such a competitive version between players A and B appears in Figure 7, although the model also could apply if the players instead were teammates who were learning from and adapting "on the fly" to one another.

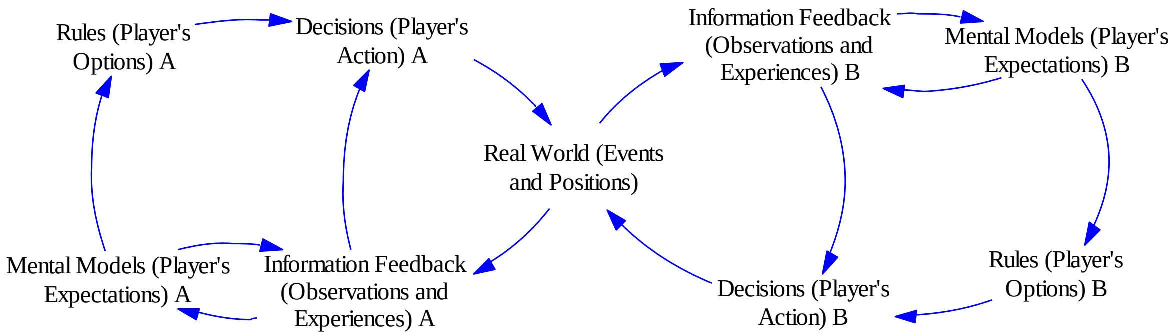


Figure 7. Causal loop drawings of competitive single- and double-loop learning

Conclusions

Individuals are complex organisms. Bar-Yam (1997) estimates the descriptive complexity of human behavior as approximating the magnitude of 10^{10} bits of data, or more. Within the context of a soccer competition, players have many independent multi-valued properties and influences, whether personal characteristics or environmental influences. Quite a number of these are, or may be treated as, constants. For example, (with the exception of the elements depicted in Figures 5 through 7, and players' pitch locations of course) none of the "Is" Characteristics listed in Table 1 is likely to change within the course of a match. We may say the same about a player's Abilities and most factors affecting his Motivation. While constants play important roles in stocks and flows modeling, SD is *not uniquely* positioned among modeling approaches to employ constants in modeling behavior.

We may say the same with respect to many "Because" Considerations set forth in Table 3. Only emerging in-match elements (such as playing conditions, minimum acceptable outcome, emerging play patterns, emerging score line, and availability of players) will vary during a match. Conversely, among the Results set forth on that table, only the teams' opening tactical alignments are fixed. Whether these elements are variable or constant, a key concern in judging their inclusion in an SD model will be their units of measure. A second important concern, as to those elements that are variable, will be the usefulness of calculus in tracing their values throughout a match.

We view the foregoing concerns as devaluing or prohibiting any broader use of SD technique beyond modeling such elements as are depicted in Figures 5 and 6. Here are some examples leading to our conclusion. Pitch locations and tactical alignments are denominated in three-dimensional space, not in one-dimensional units of measure like a player's remaining ability to run at normal speed, a possible measure of stamina. Defensive roles are not only three-dimensional but sometimes also relational, as when a player is assigned marking responsibility for a particular opponent. Even the emerging score line in a match, which may be measured in goals scored and comparatively in goals difference, traces a step function, changing exactly one goal at a time. Critically, all of the "Can"/"Does" decision-making of Table 2 translates, after taking into account inputs from the "In" and "Because" domains, into yes/no choices made by each player in each moment.

Traditional ABM addresses the non-spatial elements of the entire set of Figure 1 domains. Yes/no (1,0) values can be stored efficiently in an ABM approach. However, the *spatial* and *relational* components of competitive play require that an overall model be situated within a spatio-temporal modeling approach that incorporates some social network modeling technique, too.

Overall, the literature suggests that an agent-based approach that employs artificial intelligence and operates in a STM environment offers the most promising path. Such an ABM-led approach may employ certain SD routines, as did Größler, et al., and as are depicted in Figures 5 and 6. The SD-led, combined approaches of Akkermans, Geerlings et al., and Labedz and Stalker, likely will be less successful than other modeling methods.

Spatio-temporal modeling appears central to dynamic soccer analysis, because players' decisions and match events are determined not just by competitive actions but by their relative positions in space (i.e., on the pitch) from moment to moment. To model geometrically the curvature of a pass through a trio of third-order polynomials is an incomplete input without knowing the pitch position from which the pass was launched and the moment in time at which it was struck.

Spatio-temporal analysis however may be challenged to go beyond mere depictions of teammates' relative positions and those of opponents, so as to identify patterns of interrelationships among individuals. It may be appropriate to incorporate recent work in dynamic social network analysis (Sarkar and Moore, 2005) to bring greater insight to the patterns of observed locations of the footballers. It may not stretch too far to introduce an understanding of uncertainty topics into predictions of emergent positioning and, with them, emergent score lines.

This paper has not heretofore devoted any attention to the roles that rules enforcement (officiating) and chance play in football outcomes, but those roles are not trivial. For example, Lames and co-researchers studied more than 2,500 football goals in Europe and determined that luck (which he defined as one of six unintended events) played a role in 44% of them. Adequate modeling of football matches likely should incorporate stochastic processes.

As Sterman (2000) and Rahmandad and Sterman (2004) assert, the adequacy of any system model is contingent on the purpose of the model, the variables of interest, and the levels of precision required. This statement applies equally to an SD-only formulation and to a multi-methods simulation. Models are (and must be) simplifications of reality (Eco, 1994; Sterman, 2000), even of soccer reality, and their validation is impossible. The overriding goal of modelers should not only be to help their clients make higher quality decisions, but to inform those decisions by designing better models.

As stated at the outset of this paper, Valeriy Lobanovskyi trained as an engineer, during the early days of general systems theory and cybernetics, before pursuing his football careers as player and manager. He saw a match as a contest between two subsystems of eleven elements, moving within a defined field and subject to the laws of the game. He would contrast the effectiveness of each subsystem to “explain” wins, losses and draws. He believed that the efficiency of each subsystem was greater than the sum of the parts, so that he could apply to soccer the engineering techniques he had studied. Soccer, he concluded, was less about individuals than about coalitions and the connections among them.

In the sixty years since the Ukranian concluded his engineering studies, football has seemed at times to be much more about individuals (e.g., Puskás, Pele, Beckenbauer, Maradona, Ronaldo, Messi) and at other times (e.g., Netherlands in the 1970s, Barcelona and Spain more recently) much more about coalitions and connections. Whatever the managerial or media depictions, various theories and modeling techniques seem appropriate in studying football. Our review suggests that agent-based, spatio-temporal and dynamic network modeling approaches are most necessary.

System dynamics has a role to play in modeling some player characteristics. The competing eleven-player subsystems of a football match obviously must be considered not merely as individuals operating within a system boundary, but as adaptive multi-dimensional agents occupying continuously changing their spatio-temporal relationships to the playing field and to one another.

Systems thinking (especially as to complex adaptive systems) has an overall explanatory role in player learning, managerial strategizing and adaptation, and in the overall conceptualization of the contests. Other approaches (geometric modeling, fluid dynamics, operational reliability, and even quantum mechanics) may play roles as well. A beautiful game deserves so much and so varied attention.

Finally, here is an editorial note from the authors. To simplify our phrasing, and in keeping with the historical football accounts we cite, we have employed throughout this paper only the masculine gender. Yet we recognize the substantial contributions to football – in performance and support – increasingly made by female athletes, moms and fans. As we prepared this version of our paper on the eve of the FIFA Women’s World Cup Canada 2015 tournament, we salute the women (and men) who passionately live and enjoy the sport.

We prepared it, too, in the wake of the FIFA World Cup Brazil 2014 tournament for men. These quadrennial national team competitions remind us of the major roles that club-based football competitions, and other intervening national competitions like FIFA’s Confederations Cup and the Olympic Games, play in developing the World Cup participants. The set of environmental considerations presented in table 3 above likely requires substantial expansion when the organizational interests of for-profit football clubs are considered.

References

Abdel-Hamid TK. 2002. Modeling the dynamics of human energy regulation and its implications for obesity treatment. *System Dynamics Review* **18**(4), 431-471.

Ahmadi M, Lamjiri AK, Nevisi MM, Habibi J, Badi EK. 2003. Using a two-layered, case-based reasoning for prediction in soccer coach. In *Proceedings of 2003 International Conference on Machine Learning; Models, Technologies and Applications* (MLMTA). Las Vegas: Informs.

Anderson C, Sally D. 2013. *The Numbers Game: Why Everything You Know About Soccer Is Wrong*. Penguin Books: New York.

Argyris C. 1985. Strategy, Change, and Defensive Routines. Pitman: Boston.

Ashby, WR. 1956. *An Introduction to Cybernetics*. Chapman & Hall: London.

Bar-Yam Y. 1997. *Dynamics of complex systems*. Addison-Wesley: Reading, MA.

Bazmara M. 2014. A Novel Fuzzy Approach for Determining Best Position of Soccer Players. *International Journal of Intelligent Systems and Applications*. Published Online August 2014 in MECS (http://www.mecs-press.org/). DOI: 10.5815/ijisa.2014.09.08. [February 16, 2015]

Bialkowski A, Lucey P, Carr P, Yue Y, Sridharan S, Matthews I. 2014. *Large-scale analysis of soccer matches using spatiotemporal tracking data*. International Conference on Data Mining: Shenzen, China.

Borshchev A, Filippov A. 2004. From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. Presentation at the *22nd International Conference of the System Dynamics Society*. System Dynamics Society: Oxford, England.

Bush JWM. 2013. The aerodynamics of the beautiful game. *Sports Physics*, Ed. C. Clanet. Les Editions de l'Ecole Polytechnique: 171-192.

Carley KM. 2003. Dynamic Network Analysis in *Dynamic Social Network Modeling and Analysis: Workshop Summary and Papers*, Ronald Breiger, Kathleen Carley, and Philippa Pattison, (Eds.) Committee on Human Factors, National Research Council, National Research Council: Washington, DC.

Cavaleri S, Labedz C, Stalker G. 2012. Emergent dynamics of workforce program reductions: a hybrid multi-level analysis. *International Journal of System Dynamics Applications* **1**(1): 48-107.

Couceiro MS, Clemente FM, Martins FML, Tenreiro Machado JA. 2014. Dynamical Stability and Predictability of Football Players: The Study of One Match. *Entropy* ***16***(2): 645-674.

Dhami N. 2003. *Bend it like Beckham*. Hodder Children's Books: London.

Eco U. 1994. The impossibility of drawing a map of the empire on a scale of 1 to 1; How not to talk about soccer. In *How to travel with a salmon and other essays*. Weaver, W. translator. Harcourt Inc.: Orlando FL.

ESPN.com 2014. Available: http://www.espnfc.us/gamecast/383239/gamecast.html. [February 9, 2015].

Fédération Internationale de Football Association. 2014. Available: www.fifa.com/aboutfifa/footballdevelopment/technicalsupport/refereeing/laws-of-the-game. [April 13, 2014].

FIFA15. 2014. Available: http://en.wikipedia.org/wiki/FIFA_15. [February 9, 2015].

FIFA 2014. Available: http://en.wikipedia.org/wiki/FIFA15. [February 10, 2015].

FIFA match 45. 2014. Available: http://www.fifa.com/worldcup/matches/round=255931/match=300186469/match-report.html#nosticky. [February 13, 2014].

FIFA Technical Study Group. 2014. *Technical Report and Statistics*. FIFA World Cup Brazil™.

Forrester, J. 1961. Industrial Dynamics. Pegasus Communications: Waltham MA.

Gardner P 1996. *The Simplest Game: The Intelligent Fan's Guide to the World of Soccer*. Macmillan: New York.

Gudmundsson J, Wolle T. 2014. Football analysis using spatio-temporal tools. *Computers, Environment and Urban Systems* **47**: 16-27**.**

Hanisch KA. 2000. The impact of organizational interventions on behaviors: an examination of models of withdrawal. *Computational modeling of behavior in organizations*. D. R. Ilgen and C. L. Hulin. American Psychological Association: Washington, D.C.

Holland JH. 1992. *Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence*. MIT Press: Cambridge, MA.

Holland JH. 1995. *Hidden Order*. Perseus Books: Reading, MA.

Holland JH. 1998. *Emergence, from Order to Chaos*. Addison-Wesley: Reading, MA.

Holland JH. 2006. Studying Complex Adaptive Systems. *Journal of Systems Science and Complexity* **19**(1): 1-8.

Jenewein W, Kochanek T, Heidbrink M, Schimmelpfenning C. 2014. Learning collaboration from Tiki-Taka soccer. *Harvard Business Review Blog*. Available: https://hbr.org/2014/07/learning-collaboration-from-tika-taka-soccer. [February 28, 2015].

Kirman A. 1992. Whom or what does the representative individual represent? *Journal of Economic Perspectives* **6**(2): 117-136.

Kohler C. 2005. Power-Up: *How Japanese Video Games Gave the World an Extra Life*. BradyGames: New York.

Kukla R, Kerridge J, Willis A, Hine J. 2001. PEDFLOW: Development of an autonomous agent model of pedestrian flow. *Transportation research record: Journal of the Transportation Research Board* **1774**(1): 11-17.

Labedz CS, Berry GR. 2011. Making sense of small business growth: A "right workforce" template for growing firms. *Journal of Applied Management and Entrepreneurship* **16**(2): 61.

Labedz CS, Stalker G. 2008. Implementing a multi-level model for anticipating employee choices through a system dynamics simulation platform. Presentation at *2008 World Congress of Social Simulation* conference. Fairfax, VA.

Labedz CS, Schumaker RP, Jarmoszko AT, Freeman D. 2015. Role of contingency analysis in tactical team structure and competition in soccer. *Manuscript*.

Lames M. 2006. Glűcksspiel Fussball: Zufallseinflűsse beim Zustandekommen von Toren, in Barbara Halberschmidt and Bernd Strauss (Eds.), *Elf Freunde sollt ihr sein!? 38ste. Jahrestagung der asp. Abstracts* (S.92). Czwaline: Hamburg.

Lee J, Lee EY. 2015. Winning connections: optimal passing networks in soccer matches. Manuscript.

Lucey P, Oliver D, Carr P, Roth J, Matthews I. 2013. Assessing team strategy using spatiotemporal data. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, New York. 1366-1374.

Macal CM. 2010. To agent-based simulation from system dynamics. In *Proceedings of the 2010 Winter Simulation Conference (WSC)*: 371-382, Phoenix, AZ.

Macal CM, North MJ. 2010. Tutorial on agent-based modelling [sic] and simulation. *Journal of Simulation* **4**: 151–162

Malliaropoulos N, Papacostas E, Kiritsi O, Papalada A, Gougoulias N, Maffulli N. 2010. Posterior thigh muscle injuries in elite track and field athletes. *Am J Sports Med*. **38**(9): 1813-9.

Mortenson ME. 2006. *Geometric Modeling*. Industrial Press Inc.: New York

Parunak HVD, Savit R, Riolo RL. 1998. Agent-based modeling vs. equation-based modeling: a case study and users' guide. Multi-agent systems and Agent-based simulation. *In Proceedings of First International Workshop, MABS '98.* Paris, France: Springer Berlin Heidelberg.

Perl J. 2002. Adaptation, Antagonism, and System Dynamics. In: G. Ghent, D. Kluka & D. Jones (eds.) *Perspectives – The Multidisciplinary Series of Physical Education and Sport Science*: **4**: 105-125. Meyer & Meyer Sport: Oxford

Perl J. 2004. PerPot–a meta-model and software tool for analysis and optimisation of load-performance-interaction. *International Journal of Performance Analysis in Sport*, **4**(2): 61-73.

Perl J. 2005. Dynamic simulation of performance development: Prediction and optimal scheduling. *International Journal of Computer Science in Sport* **4.2**: 28-37.

Rahmandad H, Sterman J. 2008. Heterogeneity and network structure in the dynamics of diffusion: comparing agent-based and differential equation models. *Management Science* **54**(5): 998-1014.

RoboCup Federation. 2015. Available://www.robocup.org/about-robocup/objective. [February 8, 2015].

RWPP. 2015. The Physics of Soccer: The Magnus Effect. Available: www.real-world-physics-problems.com/physics-of-soccer.html. [February 15, 2015].

Sarkar P, Moore AW. 2005. Dynamic social network analysis using latent space models. *ACM SIGKDD Explorations Newsletter Homepage archive* (2): 31-40. ACM: New York.

Scholl HJ 2001. Agent-based and system dynamics modeling: a call for cross-study and joint research. Presented at *34th International Conference on Systems Science*. Wailea, HI: Institute of Electrical and Electronics Engineers, Inc.

Schwab DP, Olson CA. 2000. Simulating effects of pay-for-performance systems on pay-performance relationships. *Computational modeling of behavior in organizations*. DR Ilgen and CL Hulin. American Psychological Association: Washington, D.C.

Schwaninger M., Ríos JP (2008). System dynamics and cybernetics: a synergetic pair. *System Dynamics Review*, ***24***(2), 145-174.

Senge PM. 1990. *The Fifth Discipline: The Art and Practice of the Learning Organization*. Doubleday: New York.

Simon H. 1957. A Behavioral Model of Rational Choice, in *Models of Man, Social and Rational: Mathematical Essays on Rational Human Behavior in a Social Setting*. Wiley: New York.

Sterman JD. 2000. *Business Dynamics: systems thinking and modeling for a complex world****.*** McGraw-Hill Higher Education: Boston.

Sullentrop C. 2015. Game Changers: How Videogames Trained a Generation of Athletes. *Wired*. [January 22, 2015].

Tesfatsion L. 2001. Structure, behavior and market power in an evolutionary labor market with adaptive search. *Journal of economic dynamics and control* **25**: 419-457.

Tuong Manh Vu, Siebers P-O, Wagner C. 2013. Comparison of crisp systems and fuzzy systems in agent-based simulation: A case study of soccer penalties. *13th UK Workshop on Computational Intelligence (UKCI)*: 54-61.

Van der Kamp J. 2006. A field simulation study of the effectiveness of penalty kick strategies in soccer: Late alterations of kick direction increase errors and reduce accuracy. *Journal of Sports Sciences* **24**(5): 467-477.

van Olmen J, Criel B, Bhojani U, Marchal B, van Belle S, Chenge MF, Hoerée T, Pirard M, Van Damme W, Kegels G. 2012. The Health System Dynamics Framework: The introduction of an analytical model for health system analysis and its application to two case-studies. Health, Culture and Society **2**(1): 10-21.

Ventana Systems. 2003. *Vensim: the Ventana simulation environment*. Ventana Systems, Inc.: Harvard, MA. DSS32 Release 5.2.

von Bertalanffy KL. 1945. Zu einer allgemeinen Systemlehre. *Blätter für deutsche Philosophie*, 3/4. Extract in *Biologia Generalis* **19**: 139-164.

von Bertalanffy KL. 1968. *General Systems Theory: Foundations, Development, Applications*. George Braziller: New York.

Wei X., Sha L., Lucey P, Morgan S, Sridharan S. 2013. Large-scale analysis of formations in soccer. In *2013 International Conference on Digital Image Computing: Techniques and Applications (DICTA),* Hobart, Australia: IEEE: 1-8.

Weise M. 2006. No feel for the ball. Available: www.sightandsound.com/ features/812.html. [February 8, 2015].

Wiener N. 1948. *Cybernetics or control and coordination in the animal and the machine*. (2^{nd} ed., 1961, 2013). Quid Pro: New Orleans.

Wikipedia. 2015. RoboCup. http://en.wikipedia.org/wiki/RoboCup [February 9, 2015].

Wilson, J. 2013. *Inverting the Pyramid: The History of Soccer Tactics*. New York: Nation Books.

Wooldridgey M, Ciancarini P. 2001. Agent-oriented software engineering: The state of the art. In *Agent-oriented software engineering* 1-28. Springer Berlin: Heidelberg.

Zadeh LA. 1965. Fuzzy sets. *Information and Control* **8**(3): 338–353.

Appendix of formulas, definitions and simulation results

Figure 4: recovery from soft tissue injury

healing contribution from treatment = 0.015. Units: Dmnl. Healing contribution from treatment represents an additional daily recovery percentage, beyond that of the body's natural healing processes, provided through physiotherapist activity.

intrinsic healing capacity = 0.015. Units: Dmnl. Intrinsic healing capacity represents a daily recovery percentage attributable to the body's natural healing processes.

motion deficit= INTEG (-recovery rate, 20). Units: percentage of motion. Motion deficit represents the percentage of motion lost in athletes' acute, first-time, unilateral posterior thigh muscle injuries.

range of motion = 20.Units: percentage of motion. Range of motion represents the percentage of motion that may be recovered following athletes' posterior thigh muscle injuries.

recovered motion = INTEG (recovery rate, 1). Units: percentage of motion. Recovered motion Motion deficit represents the percentage of lost motion regained following unilateral posterior thigh muscle injuries.

recovery rate = range of motion*(intrinsic healing capacity + healing contribution from treatment) * Motion deficit * (Recovered motion/range of motion). Units: percentage/day. Recovery rate is the percentage by which normal motion is recovered in each time period (day).