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DEVS SIMULATION OF BELBIN'S TEAM ROLES FOR COLLABORATIVE TEAM DYNAMICS

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ABSTRACT

Belbin's team role theory identifies nine behavioral roles that, when combined, support effective collaboration. Configuring teams based on these roles is often manual, costly, and inflexible. This article presents an individual-oriented simulation model using the Discrete-EVent System Specification (DEVS) formalism to emulate group interactions shaped by Belbin roles. Each team member is modeled as an atomic entity with behavior defined by a combination of two roles. This enables controlled experimentation with different team compositions, interaction timings, and communication sequences. Simulations were conducted using synthetic data, defined under plausible assumptions based on Belbin's framework. The model enables exploration of how different configurations affect communication flow and task distribution, supporting the identification of team structures that promote balance and efficiency. Results demonstrate the potential of integrating behavioral theories with formal modeling approaches to improve team design. This work offers a flexible and extensible simulation-based method for analyzing and optimizing team dynamics.

1 INTRODUCTION

Effective teamwork is paramount to success in modern organizations, particularly within agile environments that demand high levels of collaboration, adaptability, and communication. Agile methodologies such as Scrum and Extreme Programming (XP) emphasize continuous interaction, shared responsibilities, and team flexibility, recognizing that diverse behavioral profiles significantly influence team performance (Verwijs and Russo 2023; Schwaber and Sutherland 2020).

Belbin's team role theory is an influential framework for understanding these behavioral dynamics. The theory identifies nine distinct and complementary roles, grouped into three behavioral categories that individuals can adopt in collaborative settings. Each role describes specific tendencies and interaction patterns. When strategically distributed within a team, these roles can enhance cohesion, reduce conflict, and improve collective performance (Belbin and Brown 2022). However, not all studies report consistent findings. Batenburg et al. (2013) found no evidence that role diversity improves performance in traditional teams, suggesting that the impact of team roles may be context-dependent. This variability underscores the need for simulation tools capable of evaluating team dynamics across diverse scenarios.

Furthermore, configuring effective teams using Belbin roles typically relies on personality assessments and manual analysis, which are time-consuming, expensive, and difficult to scale. Static configurations also fail to adapt to task-specific requirements or evolving communication demands.

To address these challenges, this paper introduces a simulation-based approach using the Discrete Event System Specification (DEVS) formalism (Zeigler et al. 2018) to model and analyze team dynamics according to Belbin's team role theory.

DEVS provides various advantages for modeling this kind of problems (Wainer 2009; Zeigler et al. 2018). As a hierarchical and modular formalism, it allows complex systems to be specified at multiple levels, facilitating model reuse, straightforward extension, and coupling with Experimental Frameworks to improve testing. Furthermore, DEVS is a formal method, providing facilities to translate specifications directly into executable models. Finally, its use of a continuous time base enables accurate timing representation with high precision and computational efficiency, avoiding the performance costs associated with small, discrete time steps.

Our model represents each team member with behaviors derived from role distributions, enabling controlled experimentation with various team configurations and interaction patterns. This approach supports dynamic analysis without the risks and limitations of real-world testing.

All simulations were conducted using synthetic datasets defined under plausible assumptions based on Belbin's framework and previous real experiments (Monsalves et al. 2023). These serve as a conceptual validation of the model. Preliminary results suggest that the simulation enables structured communication flow and task distribution exploration.

The remainder of this paper is organized as follows: Section 2 reviews Belbin's team role theory and the DEVS formalism. In Section 3, we describe similar approaches to the simulation of team dynamics. In Section 4, we provide a DEVS model of Belbin's Team Role to simulate collaborative team dynamics. Section 5 describes the simulation design. Simulation results are discussed in Section 6. Finally, Section 7 concludes the paper with directions for future work.

2 BACKGROUND

2.1 Belbin's Team Role Theory

Belbin's team role theory has become one of the tools of choice to build effective teams, based on the preconception that it was designed to predict the success of work teams (Belbin and Brown 2022; Marian 2023). Belbin's team role theory postulates that every effective work team must achieve a balance between the different roles assumed by its members. Meredith Belbin identified nine team roles, grouped into three behavioral profiles: social roles, mental roles, and action roles (Belbin 2010). These roles are not fixed personality traits, but tendencies that individuals exhibit in teamwork environments (Da Costa Porto 2023). The core premise is that a balanced composition improves overall performance, as each role's strengths offset the weaknesses of others, leading to better communication and cohesion (Belbin 2010; Twardochleb 2017; Belbin and Brown 2022). A summary of these nine roles is presented in Table 1.

Table 1: Belbin roles classified by functional profiles. Adapted from Belbin and Brown (2022).

Profile	Role	Strengths	Allowable Weaknesses
Social	Coordinator	Confident, clarifies goals, promotes decision-making	Can be perceived as manipulative or delegating too much
	Resource Investigator	Extroverted, explores opportunities, develops contacts	May lose interest after initial enthusiasm
	Teamworker	Cooperative, perceptive, diplomatic	Indecisive in crunch situations
Mental	Plant	Creative, solves difficult problems	May ignore details, too preoccupied to communicate
	Monitor Evaluator	Sober, strategic, discerning	Lacks drive or ability to inspire others
	Specialist	Dedicated, provides in-depth knowledge	Narrow contributor, dwells on technicalities
Action	Shaper	Dynamic, thrives under pressure, challenges inertia	Prone to provocation, offends others
	Implementer	Disciplined, reliable, turns ideas into action	Inflexible, slow to respond to new possibilities
	Completer Finisher	Painstaking, anxious, searches out errors	Worries unduly, reluctant to delegate

To identify Belbin roles in individuals, the methodology proposes using a team role self-perception questionnaire, in which each team member completes an assessment to reveal their preferred behavioral roles when working with others. This questionnaire returns the percentiles associated with each role for an individual, which express their strengths when performing in teamwork situations. It is common for an individual to have several predominant roles (Monsalves, Cornide-Reyes, and Riquelme 2023), so in this article, we will focus on the two dominant roles for each individual.

The Belbin model allows for profiling members to form balanced teams, ensuring necessary roles are represented while avoiding the oversaturation or absence of any single role (Newman 2011; Griffiths et al. 2008). This conscious assignment based on natural strengths is argued to foster team synergy and align tasks effectively (Griffiths et al. 2008; Belbin and Brown 2022). The model's principles are applied across various fields. In software development, for example, effective role management is crucial, as inadequate team composition can lead to conflicts and project failure (Zainal et al. 2020). Similarly, in professional contexts, studies have found a significant correlation between Belbin role diversity and measured team effectiveness (Adamis et al. 2023). Higher education has also adopted Belbin's theory to form and study student teams in project-based and collaborative learning. Monsalves et al. (2023) explored the relationships between Belbin behavioral roles, affinity sociograms, and social interactions in collaborative agile teams formed by university students. Using the Lego Serious Play methodology, the researchers identified behavioral patterns associated with natural social and action roles, showing how these interactions influence team dynamics. Similarly, Flores Ureba et al. (2022) analyzed the influence of Belbin roles on the quality of collaborative learning with 149 students in an Introduction to Business course. The results indicated that groups balanced according to Belbin's theory facilitated greater homogeneity in grades and improved overall group performance. In contrast, Garcia-Ramirez (2020) found more nuanced results when studying the relationship between Belbin roles and performance, in road design courses.

There are innovations related to Belbin's theory. In Tamayo Avila et al. (2022), the authors present the Agile Software Engineers Stick Together framework, which combines team-based learning, problem-based learning, and role-playing dynamics to train agile collaboration. Aranzabal et al. (2022) introduced a method for forming balanced teams based on Belbin roles in a project-based learning environment, comparing their performance to teams whose members had self-selected. In addition, satisfaction surveys revealed further benefits: students in Belbin-based teams attended classes more regularly, required less individual study time, and showed more significant interest in the subject.

These findings support the Belbin model's applicability, suggesting leaders can increase team effectiveness by balancing role distribution. However, not all studies show positive results. Batenburg et al. (2013) found no evidence that mere role diversity improves performance, which indicates that the impact of roles depends on the context and implementation. Therefore, simulating diverse scenarios with different role distributions can help identify appropriate configurations for specific contexts, optimizing resources in controlled experiments.

2.2 DEVS

The Discrete Event System Specification (DEVS) is a formalism for the modeling and simulation of discrete event dynamic systems (Zeigler et al. 2018). DEVS allows systems to be described using two types of elements: atomic and coupled models. This work uses the *DEVS with ports* variant, which defines explicit input and output channels, enabling direct and structured communication between models through designated ports.

Atomic models are the most elemental entities to build representations of systems. Their states change when receiving an input event or after a time delay. Coupled models, conversely, enable hierarchical model construction by grouping several DEVS models into a compound one, allowing model reuse. Coupled models can be regarded, due to the closure property, as another DEVS model that is behaviorally equivalent to an atomic model (Wainer 2009).

Coupled models may have their own input and output ports. Upon the arrival of an external event, a coupled model reroutes the input to one or more of its components (*EIC*). In addition, when a component produces an output, it must be mapped as another component's input (*IC*) or as an output of the coupled model itself (*EOC*). While atomic models represent the behavior of individual entities, coupled models define the structure and interactions within the system.

A formal definition of an atomic model with ports is described by the tuple (Zeigler et al. 2018):

$$M = \langle X, Y, S, \delta_{int}, \delta_{ext}, \lambda, ta \rangle$$

where:

- $X = \{(p, v) \mid p \in InPorts, v \in X_p\}$ is the set of input events, where *InPorts* is the set of input ports and X_p corresponds to the set of values for the input ports;
- $Y = \{(p, v) \mid p \in OutPorts, v \in Y_p\}$ is the set of output events, where *OutPorts* represents the set of output ports and Y_p represents the set of values for the output ports;
- S is the set of sequential *states*;
- $\delta_{ext} : Q \times X \rightarrow S$ is the *external transition function*, where $Q = \{(s, e) \mid s \in S, e \in [0, ta(s)]\}$ and e is the elapsed time since the last state transition;
- $\delta_{int} : S \rightarrow S$ is the *internal transition function*;
- $\lambda : S \rightarrow Y$ is the *output function*;
- $ta : S \rightarrow R_0^+$ is the *time advance function*.

A coupled model is formally defined as (Zeigler et al. 2018; Wainer 2009):

$$CM = \langle X_{\text{self}}, Y_{\text{self}}, D, \{M_d\}, \text{EIC}, \text{EOC}, \text{IC}, \text{Select} \rangle$$

where:

- X_{self}: is the set of input ports and values for the coupled model itself.
- Y_{self}: is the set of output ports and values for the coupled model itself.
- D: is the set of unique names for the component models contained within the coupled model.
- $\{M_d\}$: is the set of component DEVS models, where for each name $d \in D$, M_d is a DEVS model.
- $EIC \subseteq \{((Self, p_{\text{in\_self}}), (d, p_{\text{in\_d}})) \mid p_{\text{in\_self}} \in \text{InPorts}_{\text{self}}, d \in D, p_{\text{in\_d}} \in \text{InPorts}_d\}$ is the External Input Coupling set. It connects the coupled model's own input ports to the input ports of its internal components.
- $EOC \subseteq \{((d, p_{\text{out\_d}}), (Self, p_{\text{out\_self}})) \mid d \in D, p_{\text{out\_d}} \in \text{OutPorts}_d, p_{\text{out\_self}} \in \text{OutPorts}_{\text{self}}\}$ is the External Output Coupling set. It connects the output ports of internal components to the coupled model's own output ports.
- $IC \subseteq \{((i, p_{\text{out\_i}}), (j, p_{\text{in\_j}})) \mid i, j \in D, p_{\text{out\_i}} \in \text{OutPorts}_i, p_{\text{in\_j}} \in \text{InPorts}_j\}$ is the Internal Coupling set. It connects the output port of one internal component to the input port of another internal component.
- Select: is the tie-breaking function that selects which component to activate first from a set of components scheduled for simultaneous events.

In summary, the features of the DEVS formalism make it well-suited for modeling the collaborative dynamics described by Belbin's theory. The modular and hierarchical structure is ideal for representing individual team members and their nested interactions within a team. Furthermore, using ports provides a natural mechanism for modeling the directed communication sequences central to this work, while the continuous time base allows for precise control over interaction timings. These capabilities, provide the foundation for the specific model of team dynamics presented in Section 4.

3 RELATED WORK

Understanding and improving team collaboration has long been a topic of interest in organizational theory and computational modeling. Among various frameworks, Belbin's team role theory has gained wide adoption due to its ability to explain group dynamics through a structured set of nine behavioral roles (Flores Ureba et al. 2022).

From a simulation perspective, agent-based models (ABM) have been a natural choice for studying team dynamics. These models simulate autonomous agents with individual behavior and goals, often incorporating psychological constructs, allowing us to observe the emergence of complex phenomena such as cooperation, leadership emergence, and team adaptation. Farhangian (2018) examined the influence of Myers–Briggs Type Indicator (MBTI) personality types on team behavior using ABMs, delivering insights into how personality affects team dynamics and performance outcomes. Jayashankar and Balan (2024) used a combination of ABM with generative adversarial networks (GAN), to generate synthetic data for the simulation of employee interactions, enabling the analysis of team performance, flexibility, and workflow optimization. ABM has also been used to study team formation dynamics; e.g., Yee (2017) modeled students' self-controlled team-building behavior to understand how population size and heterogeneity influence group stabilization, and Archibold et al. (2019) highlighted the role of ABMs in organizational research for studying emergent phenomena in team and group dynamics. These approaches show the potential of ABM to study team performance, although they often emphasize formation or structural efficiency over communication sequences or role-based behavioral modeling. However, they do not rely on formal discrete-event specifications.

DEVS has been increasingly applied to simulating human behavior and social dynamics. Several studies have demonstrated the applicability of DEVS and Cell-DEVS (a Cellular Automata extension to DEVS) in this domain. Bouanan et al. (2014) used DEVS and Cell-DEVS to model the diffusion of information through social networks, highlighting the impact of individual receptivity and network structure on the spread of information. Khalil and Wainer (2020) emphasized the advantages of Cell-DEVS in modeling and visualizing a wide variety of social systems, arguing that it overcomes the limitations of other modeling approaches through localized interaction rules and formal semantics. Similarly, Seck et al. (2007) proposed a DEVS-based framework to simulate human behavior in military contexts, accounting for moderating factors such as personality and stress. Behl et al. (2018) applied Cell-DEVS to model behavioral change during product launches, showing how individual attributes and interaction frequency affect decision-making.

The cited studies show DEVS is suitable for simulating group dynamics. While ABM is a common choice, DEVS offers advantages for this paper's focus on formal, timed communication sequences, providing precise specifications and timing control that some ABM approaches lack. Despite its suitability, no prior work has combined DEVS with Belbin's role theory. This paper addresses that gap, using DEVS's hierarchical and formal capabilities to provide the foundation for the model in Section 4.

4 DEVS MODEL

4.1 Model Overview

This proposal models collaborative teamwork processes based on Belbin team roles using the DEVS formalism. As observed in Figure 1, each team member is represented as an atomic DEVS model, whereas the whole team is modeled as a coupled DEVS model representing the interaction structure among members. Members are connected via input/output ports, allowing directed message exchange between any pair of participants.

The model rationale is that team members talk to the rest by turns. The current speaker selects the next one by evaluating all team members, choosing the person with the highest role compatibility based on a predefined affinity matrix and their personality profiles.

A token-passing mechanism governs speaking turns. At any time, only one team member is allowed to be "Talking". Once their speaking time elapses, the token is passed to another member, enforcing

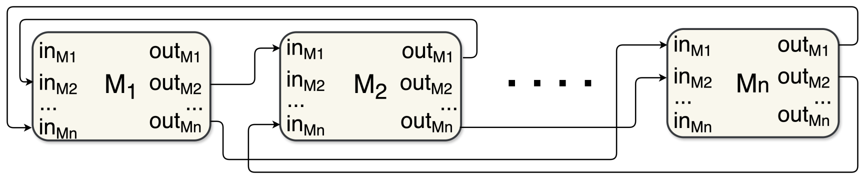


Figure 1: Teamwork DEVS model

sequential, non-interruptive communication, mimicking structured team discussions. Silent periods (where no member is speaking) and noise (where several members speak simultaneously) are omitted from the simulation.

A member's speaking duration is dynamically computed based on role compatibility with the previous speaker, considering both participants' roles, the speaker's weights, and a predefined affinity matrix.

4.2 Model Definition

Using the DEVS formalism, a collaborative process based on Belbin's team role theory is defined as a coupled DEVS model composed of n atomic submodels, each representing a team member. Each team member is connected to all others through dedicated input/output port, allowing directed exchange of the token between any pair of participants and also to design the next speaker.

The teamwork is formally defined as a coupled model as:

$$TeamWork = \langle X, Y, D, \{M_d\}, EIC, EOC, IC, Select \rangle$$

with:

$X = Y = \emptyset$ since the team only communicates internally.

$D = \{M_1, M_2, \ldots, M_n\}$ where n is the amount of team members.

$\{M_d\}_{d \in D} = \{M_{Member_1}, M_{Member_2}, \ldots, M_{Member_n}\}$.

$EIC = EOC = \emptyset$, as there is no interaction with external models.

$IC \subseteq \{((\text{Member}_i, \text{out}_j), (\text{Member}_j, \text{in}_i)) \mid \forall i, j \text{ with } i \neq j\}$ defines the connection among members through input/output ports.

$\text{Select} = \min_{i \in D}(i)$ should simultaneous events occur, the team member with the lowest index is chosen; however, as only one team member speaks at a time, this function is unused in practice.

The formal definition of team members (as atomic models) is:

$$\text{Member} = \langle X, Y, S, \delta_{\text{int}}, \delta_{\text{ext}}, \lambda, \text{ta} \rangle$$

where:

$X = \{in_i \mid i \in D\}$ is the set of input ports. An event on port in_i signifies receiving a speaking token. The sender's identity, i, is inferred from the port on which the event arrives.

$Y = \{out_j \mid j \in D\}$ is the set of output ports. An event is sent on port out_j to pass the speaking token to the selected member j. The output itself carries no data.

$S = \text{Phase} \times \text{Name} \times \text{Roles} \times \text{Weights} \times \text{TeamRoster} \times \text{AccumulatedTime} \times \sigma$, is the set of sequential states where:

$\text{Phase} \in \{\text{“Talking”}, \text{“Passivated”}\}$ is the member's current activity.

Name: A unique identifier for the member.

$\text{Roles} = R \times R$ is a tuple composed the member's two dominant Belbin roles, with:

$R = \{$“Coordinator”, “Resource Investigator”, “Teamworker”, “Plant”, “Monitor Evaluator”, “Specialist”, “Shaper”, “Implementer”, “Completer Finisher”$\}$ is the set of all possible roles.

$\text{Weights} = \mathbb{R} \times \mathbb{R}$: A tuple composed by the weights of both roles.

TeamRoster: A data structure containing the necessary information about all other team members. It is used to look up the attributes of other members. Contains the data to compute a communication recipient.

AccumulatedTime $\in \mathbb{R}_0^+$: Allows to track the member's total speaking time.

$\sigma \in \mathbb{R}_0^+$ is the remaining time in the current phase.

$\delta_{int} S \rightarrow S$ is the internal transition function. When triggered ($\sigma = 0$), this function allows a member to transition from "Talking" to "Passivated". Given a state $s \in S$ where s.Phase = "Talking", produces a new state s' where s'.Phase = "Passivated", s'.AccumulatedTime = s.AccumulatedTime + $ta(s)$, and $s'.\sigma = \infty$. All other elements of the state remain unchanged.

$\delta_{ext} : Q \times X \rightarrow S$ is the external transition function, where $Q = \{(s,e) \mid s \in S, 0 \leq e \leq \mathrm{ta}(s)\}$. When a "Passivated" member receives a token on input port in_i, it transitions to "Talking." The sender's Name is identified through i and its internal `TeamRoster` is searched to retrieve the sender's roles. The new speaking duration, σ', is then calculated. The process is as follows: First, a base compatibility score is determined by looking up the affinity between the sender's roles and the receiver's roles in a predefined affinity matrix; then, the score is adjusted using the receiver's role `Weights` to reflect their personal strengths; Then, the final weighted score is scaled to a predefined time range to produce the final speaking duration σ'.

$\lambda : S \rightarrow Y$ is the output function. When a member finishes speaking ($\sigma = 0$), this function performs the next-speaker selection logic. Reflects the behavior of the `evalNextSpeaker()` method found in the implementation by iterating through the `TeamRoster`, calculating a compatibility score for each candidate, and selecting the member j with the highest score. Finally, it activates the output port out_j.

$ta : S \rightarrow \mathbb{R}_0^+ \cup \{\infty\}$ is the time advance function. It returns the value of σ from the current state: $\mathrm{ta}(s) = s.\sigma$. If the state is "Talking", then σ is computed as explained in Section 4.1.

The formal specification above provides a complete and self-contained definition of the Member model's behavior. For readers interested in the specific computational details, the full model implementation in DEVS-Suite framework (Kim et al. 2009) that was used to generate the experimental results is available in our GitHub repository.

5 EXPERIMENTS AND RESULTS

We defined and executed three scenarios to evaluate the proposed DEVS-based simulation model. The primary objective of the experiments is to observe how team composition (based on Belbin roles and their associated weights) affects communication dynamics. Each simulated scenario is configured by a set of parameters: the team members (each identified by an ID, name, two Belbin roles, and their respective weights) and an additional role affinity matrix used to compute the sequence of the different speakers. All these model parameters are synthetic and based on reasonable assumptions grounded in Belbin theory and team behavior literature (Monsalves et al. 2023). While not empirically derived, these parameters were chosen to support plausible and consistent behavior within the scope of exploratory simulation. Only team member roles and their corresponding weights are presented below.

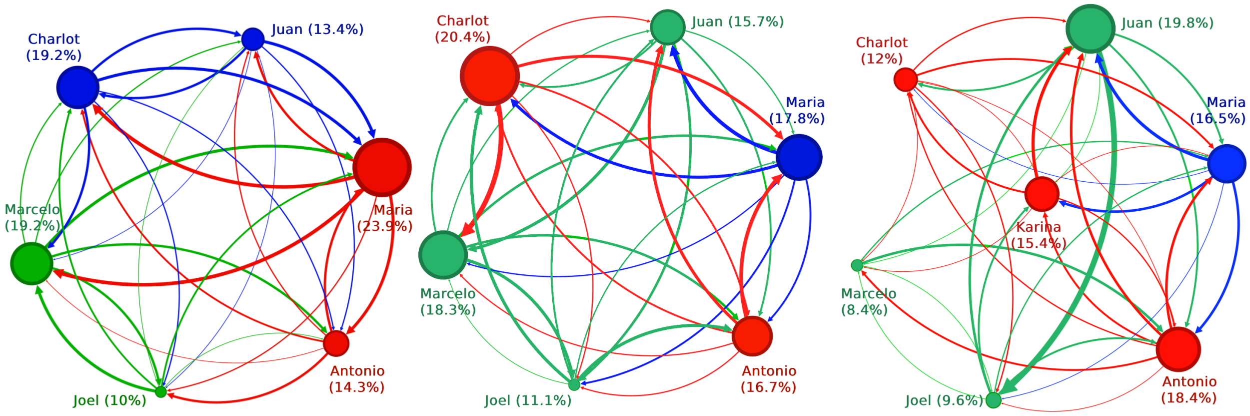
5.1 Scenario 1

This first scenario models a team composed of six members. Table 2 presents the team configuration (identifier, role composition, and relative role weights for each member) and speaking times (number of interventions, total and percentage of speaking times), which are measured in time units.

Maria emerged as the most active member, in terms of number of interventions and total speaking time, followed by Marcelo and Charlot. However, note that although these last two spoke the same, Marcelo intervened once more than Charlot, so on average the former's interventions were shorter than those of the latter. The one who intervened and spoke the least was Joel.

Table 2: Team configuration, number of interventions, and speaking times for Scenario 1.

Team configuration					**Speaking time**		
Name	**Role 1**	**Weight 1**	**Role 2**	**Weight 2**	**Interventions**	**Total**	**%**
Juan	Specialist	0.60	Team Worker	0.40	13	403.00	13.4
Maria	Coordinator	0.81	Implementer	0.20	22	720.13	23.9
Charlot	Monitor Evaluator	0.82	Specialist	0.28	16	579.70	19.2
Antonio	Coordinator	0.50	Plant	0.45	14	432.25	14.3
Marcelo	Shaper	0.80	Implementer	0.30	17	579.70	19.2
Joel	Completer Finisher	0.45	Plant	0.26	12	299.98	10.0
				Total	94	3014.76	100



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

Figure 2: Communication networks. Colors represent the profile of the dominant role (social: red, mental: blue, action: green). Node sizes represent the proportion of total speaking times, and edge thicknesses the number of interventions from one person to another.

Interventions between members are represented as relationships in the communication network in Figure 2a. Each intervention from member a is directed to member b, which is represented as a directed edge (a,b) in the network. The thickness of each edge represents the number of interventions between each pair of members. Furthermore, the size of each node represents the total speaking time of the participant.

5.2 Scenario 2

In this variant, the team configuration is modified by changing some roles while maintaining similar weight distributions. The updated parameters (shown in italics) are presented in Table 3.

Now, Maria and Charlot make the most contributions, although Charlot spends the most time speaking. Once again, Joel participates the least. The communication network for this case is shown in Figure 2b.

5.3 Scenario 3

This scenario modifies the team structure by adding a seventh member but keeps the same configuration for existing team members from Scenario 2. The purpose of this modification is to observe how increasing the team size (while maintaining diversity in role combinations) affects communication flow, speaking turns, and speaking time distribution. The new configuration can be observed in Table 4. Karina, the newly added member, is shown in italics.

Table 3: Team configuration, number of interventions, and speaking times for Scenario 2.

Team configuration					**Speaking time**		
Name	**Role 1**	**Weight 1**	**Role 2**	**Weight 2**	**Interventions**	**Total**	**%**
Juan	*Completer Finisher*	0.60	Team Worker	0.40	17	476.00	15.7
Maria	*Specialist*	0.81	Implementer	0.20	19	537.32	17.8
Charlot	*Coordinator*	0.82	Specialist	0.28	19	616.00	20.4
Antonio	Coordinator	0.50	Plant	0.45	18	504.45	16.7
Marcelo	Shaper	0.80	Implementer	0.30	18	554.40	18.3
Joel	Completer Finisher	0.45	Plant	0.26	14	335.12	11.1
				Total	105	3023.29	100

Table 4: Team configuration, number of interventions, and speaking times for Scenario 3.

Team configuration					**Speaking time**		
Name	**Role 1**	**Weight 1**	**Role 2**	**Weight 2**	**Interventions**	**Total**	**%**
Juan	Completer Finisher	0.60	Team Worker	0.40	20	600.00	19.79
Maria	Specialist	0.81	Implementer	0.20	14	499.95	16.49
Charlot	Coordinator	0.82	Specialist	0.28	9	363.00	11.97
Antonio	Coordinator	0.50	Plant	0.45	16	557.18	18.37
Marcelo	Shaper	0.80	Implementer	0.30	7	254.10	8.38
Joel	Completer Finisher	0.45	Plant	0.26	13	290.75	9.59
Karina	*Resource Investigator*	*0.67*	*Shaper*	*0.51*	12	467.28	15.41
				Total	91	3032.25	100

Compared to Scenario 2, the only difference lies in the introduction of Karina, whose roles (*Shaper* and *Resource Investigator*) are both of high-energy and outward-facing. Note that this inclusion significantly alters the group dynamics. In this case, Juan, the second-least active in Scenario 1, is now the most active in terms of interventions and speaking time. Furthermore, Joel is no longer the most inactive, having been replaced by Marcelo. The communication network for this case is shown in Figure 2c.

6 DISCUSSION

As mentioned earlier, the simulations performed in this work were exploratory, and all parameters are synthetic and not empirically calibrated. However, they were defined using assumptions considered reasonable to reflect plausible team interactions, as previously mentioned.

Our model simplifies communication as one-to-one interactions. Broadcast messaging—where one member addresses two or more—is not supported, though common in real teams.

Based on the results from Section 5, a clear impact of Belbin roles on communication patterns can be observed. Roles associated with Social and Action profiles, such as Coordinator or Shaper, tend to exhibit greater participation (e.g., Maria and Marcelo in Scenario 1; Maria, Marcelo, and Charlot in Scenario 2). However, the introduction of participants with different roles or low weights in their dominant roles may disrupt this pattern, as seen in Scenario 3. It is also notable that members with Social or Action profiles but low dominance (e.g., Joel, with a weight of only 0.45 for the Completer Finisher role) show limited group participation—sometimes even less than members with Mental profile roles. The predominance of red-colored nodes from Figure 2a (representing social roles) at the center of the interaction networks confirms Belbin's premise that social roles facilitate team communication.

The role modifications in Scenario 2, as shown in Table 3, led to observable changes in communication dynamics. Charlot's transition from Monitor Evaluator (Mental) to Coordinator (Social) resulted in an increase in both interaction frequency (from 16 to 19 interventions) and total speaking time (from 579.70

to 616.00 units). Similarly, Juan's role change from Specialist (Mental) to Completer Finisher (Action) led to an increase in interventions (from 17 to 20) and speaking time (from 476 to 600 units). Conversely, Maria's transition from Coordinator to Specialist resulted in a reduction in her interventions (from 22 to 19) and speaking time (from 720.13 to 537.32 units), supporting Belbin's assertion that Specialists tend to offer direct contributions rather than promote extended discussions. The network shown in Figure 2b reveals a more distributed pattern than in Scenario 1. While Coordinator roles still occupy central positions, the communication links are more evenly weighted, suggesting that a well-balanced distribution of social roles can promote more equitable communication. Joel, the least active member, has the lowest role weight, showing an unclear role profile, which seems to hinder his integration into the team.

Table 4 shows that the inclusion of Karina in Scenario 3 introduced the roles of Resource Investigator and Shaper, both characterized by dynamism and initiative. While Karina does not stand out in terms of total speaking time or number of interventions, she achieved the second-highest average speaking time per intervention (38.9 units), surpassed only by Charlot (40.3), which highlights the assertiveness typically associated with these roles. Simultaneously, Marcelo's participation dropped significantly (from 18 to 7 interventions), suggesting possible competition between individuals with the Shaper role. It is also noteworthy that Karina's inclusion in an activity of the same duration as previous scenarios resulted in the absence of certain interactions—for example, the missing edge from Charlot to Marcelo in Figure 2c.

The model simulates the selection of the next speaker using a compatibility function between roles, and the results suggest that this affinity guides the flow of communication. Figure 2 shows patterns in which certain connections are more frequent or intense—potentially between compatible roles (e.g., Coordinators and Shapers interacting to drive decisions). This may lead to subgroup formation or conversational centralization, thus validating through simulation a key aspect of Belbin's theory: role relationships shape group dynamics. The simulations also highlight the potential imbalance inherent in certain configurations. The concentration of speaking time in just two members in Scenario 2 (Marcelo and Charlot, 38.7% of the total) could, in real-world contexts, limit the diversity of perspectives. These findings reinforce Belbin's central thesis: teams should avoid the overrepresentation of certain roles while ensuring adequate representation of social roles to facilitate communication flow.

The proposed DEVS model is validated as a tool for exploring hypothetical team compositions. It enables visualization and quantification of how different combinations of Belbin roles can either facilitate or hinder balanced communication flows and, potentially, team efficiency—one of the core pillars of the original theory.

7 CONCLUSIONS AND FUTURE WORK

This work has presented a DEVS-based simulation model to analyze team dynamics according to Belbin's team role theory. The model's design enables scalability to teams of arbitrary size and supports experimentation under varying interaction parameters. The results demonstrate that the DEVS formalism provides a suitable framework for simulating team interactions, enabling observation of how different role configurations affect communication patterns and the distribution of speaking turns among team members. Through three experimental scenarios, we visualized how roles influence communication flow. The simulations confirm key aspects of Belbin's theory: social roles—particularly Coordinators—facilitate communication by occupying central positions within interaction networks; Action roles such as Shapers show high levels of participation; and role transitions can alter communication patterns. The model also reveals the potential risks of role imbalance, where certain profiles may be overrepresented or underrepresented.

In industrial settings, this approach offers strategic value for human resources and project management departments. Organizations may use such models as predictive tools to optimize team composition prior to deployment, reducing costs associated with later restructuring and minimizing the impact of suboptimal configurations.

Future work will focus on refining the simulator using empirical data on speaking time, interactions, and team performance in real-world settings. This will enable more precise calibration of role affinities and interaction parameters. Also, we plan to extend the model to account for task-specific contexts and to incorporate temporal dynamics that simulate how interactions evolve throughout the project lifecycle. Additionally, we plan to include more complex behavior, such as members addressing more than one recipient at a time and members interrupting one another.

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