A Nonlinear Multicriteria Model for Team Effectiveness

Isabel Dórdio Dimas[1,2](✉), Humberto Rocha[3,4], Teresa Rebelo[5,6], and Paulo Renato Lourenço[5,6]

[1] ESTGA, Universidade de Aveiro, 3750-127 Águeda, Portugal
[2] GOVCOPP, Universidade de Aveiro, 3810-193 Aveiro, Portugal
idimas@ua.pt
[3] FEUC, Universidade de Coimbra, 3004-512 Coimbra, Portugal
[4] INESC-Coimbra, 3030-290 Coimbra, Portugal
hrocha@mat.uc.pt
[5] IPCDVS, Universidade de Coimbra, 3001-802 Coimbra, Portugal
[6] FPCEUC, Universidade de Coimbra, 3000-115 Coimbra, Portugal
{terebelo,prenato}@fpce.uc.pt

Abstract. The study of team effectiveness has received significant attention in recent years. Team effectiveness is an important subject since teams play an increasingly decisive role on modern organizations. This study is inherently a multicriteria problem as different criteria are typically required to assess team effectiveness. Among the different aspects of interest on the study of team effectiveness one of the utmost importance is to acknowledge, as accurately as possible, the relationships that team resources and team processes establish with team effectiveness. Typically, these relationships are studied using linear models which fail to explain the complexity inherent to group phenomena. In this study we propose a novel approach using radial basis functions to construct a multicriteria nonlinear model to more accurately capture the relationships between the team resources/processes and team effectiveness. By combining principal component analysis, radial basis functions interpolation, and cross-validation for model parameter tuning, we obtained a data fitting method that generated an approximate response with reliable trend predictions between the given data points.

Keywords: Team effectiveness · Multicriteria · Radial basis functions · Cross-validation

1 Introduction

Teams of individuals working together to achieve a common goal are, nowadays, a central part of daily life on modern organizations [24]. Hence, over the last four decades, the use of teams as a way of structuring activities has grown enormously [29]. This derives in part from the fact that teamwork seems to be superior in many situations, namely when the tasks and the problems are

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complex [23]. Moreover, groups appear to be an effective answer to the challenges posed by the actual uncertain and complex environments [29].

Given the fact that teams are created with the purpose of generating value for the organizations, the study of team effectiveness has received a significant attention in recent years [19]. The literature is consensual about the need to consider different criteria to assess effectiveness [16,19] that can be integrated into five dimensions: (i) economic – integrates efficiency and productivity and is related to the team goals achievement; (ii) social – relates to the extend to which the group experience contributes to members' well-being; (iii) political – concerns reputation and legitimacy as assessed by the teams' stakeholders; (iv) systemic – relates to the willingness of members to remain in the team in the future; (v) innovation – concerns the teams' ability to rethink on current processes and to develop innovative solutions [2].

The conceptualization of team effectiveness that is dominant in the literature is the Input–Process–Output (I–P–O) model formulated by McGrath [25]: *inputs* refer to the composition of the team in terms of the individual, team and organizational resources; *processes* refer to activities that team members engage in, combining their resources to manage the tasks; *outputs* concern team results as conceptualized above. Team dimension and team autonomy are examples of team inputs. Examples of processes include team resilience and team learning.

It is of the utmost importance to acknowledge, as accurately as possible, the relationships that team resources and team processes establish with team effectiveness. Typically, these relationships are treated as linear and studied accordingly. However, it has been reported that the relationship between some of the team characteristics/processes and team effectiveness might not be linear. E.g., Bunderson and Sutcliffe reported that too much emphasis on learning can compromise efficiency because it detracts the team from results [8]. Using multiple linear regression models, it is possible to capture the previous study findings for lower levels of team learning, for which increasing the team learning levels would correspond to an increase of team effectiveness. However, for higher levels of team learning, a linear model will fail to capture the previous findings since it will continue to display an increase of team effectiveness when increasing the values of learning levels.

In this study we propose a novel approach using radial basis functions to construct a multicriteria nonlinear model attempting to more accurately capture the relationships between the team resources/processes and team effectiveness. Radial basis function (RBF) methods are interpolation methods, i.e. they exactly fit each data point. There are many different mathematical models that can easily fit a data set exactly no matter how the data points are distributed.However, building a response by using a scarce number of poorly distributed data points is very unreliable, yet necessary in many problems. There is a wide range of applications where RBF interpolation methods were successfully applied, including aeronautics [30,33], radiotherapy [32,34] and meteorology [7]. In most of the applications, RBF models are used as predictive tools. Their good predictive ability underlies their capacity to serve as surrogates that mimic well the unknown responses. RBFs surrogate features are used in this study to capture the trends between the team resources/processes and team effectiveness.

2 Materials and Methods

2.1 Problem Features

In this study, the assessment of team effectiveness is based on four criteria – performance (economic dimension), quality of the group experience (social dimension), viability (systemic dimension) and team process improvement (innovation dimension). Data concerning the political dimension was not available for this study. It is straightforward to formulate a multicriteria mathematical optimization model by considering team effectiveness as a weighted sum of these four criteria. Equal weights were considered for the different criteria.

Team effectiveness will be considered as the result of the presence of six variables: three of them can be conceived as inputs in I-P-O Model, i.e., team dimension, transformational leadership and team autonomy, and the remaining three, team resilience, supportive behaviors and team learning, as processes. Each variable will be briefly described as follows.

Team size corresponds to the number of elements that a team has. In accordance to the literature on team composition, well-composed teams are as small and diverse as possible [17]. Hence, coordinating and integrating individual contributions in large size teams is harder than on small ones, resulting, as a consequence, in negative outcomes.

Transformational leadership can be defined as a leadership style that encourages followers to do more than they originally expected, broadening and changing their interests and leading to conscientiousness and acceptance of the group's purposes [3]. Carless, Wearing and Mann [10] described transformational leaders as those who exhibit the following seven behaviours: they (1) communicate a vision; (2) develop staff; (3) provide support for them to work towards their objectives through coordinated team work; (4) empower staff; (5) are innovative by using non-conventional strategies to achieve their goals; (6) lead by example; (7) are charismatic. A positive association of transformational leadership with team results is suggested in literature (e.g., [4,18]).

Team autonomy can be defined as the level of freedom and independence that a team has in deciding how to carry out the tasks [21] and has been conceived as a critical element of team performance (e.g., [12,21]).

Team resilience is the ability of the team not only to recover from stressful events but also to grow and learn from the adversity [39]. It is an adaptive process, which enables teams to manage difficulties in a positive way, without jeopardizing cohesion and team results. Given that work environments are becoming more and more challenging, team resilience has been related with positive consequences for teams [37].

Supportive behaviors can be defined as the extend to which team members provide voluntary assistance to each other [2]. This concept encompasses both instrumental (tangible help that members may provide to each other) and emotional (members' actions that make other members feel appreciated and that bolster their selfworth) supports. It has has been related to positive team outcomes (e.g., [2,11]).

Finally, team learning can be conceived as a continuous process of reflection and action, characterized by behaviors like seeking feedback, exploring, experimenting, reflecting, and discussing errors and unexpected outcomes [15]. Previous research presented team learning as a crucial process of adaptation of teams to their environment and highlighted its importance in goals achievement (e.g., [14,15]).

2.2 Sample

A quantitative study with a cross-sectional design was conducted in which we surveyed teams from different companies, sectors (e.g., industrial, services) and geographical areas (north and center of Portugal). In line with Cohen and Bailey's definition of group [12], teams had to meet the following criteria to be included in the sample: teams must consist of at least 3 members (1), who are perceived by themselves and others as a team (2), and who interact regularly and interdependently to accomplish a common goal (3). In each company, we had to collect two types of information: the team members' questionnaires and the team leaders' questionnaires. Team members were surveyed about transformational leadership, team autonomy, team resilience, supportive behaviors, team learning and quality of the group experience, whereas team leaders were surveyed about team size, team viability, team performance and team process improvement.

Data was collected using two different strategies. In the majority of the organizations, the questionnaires were collected by a person of the organization, with a strategic relationship with the employees, previously instructed by a research team member. For the organizations where this strategy was not viable, the questionnaires were filled online via an electronic platform, with the link being provided to the participants. In both cases, the anonymity and the confidentiality of the answers were guaranteed.

Surveys were collected from 653 members of 117 workgroups and their respective leaders from nine Portuguese organizations. Teams were composed of 9.0 members on average (SD = 9.15). Questionnaires with more than 10 % answers missing were eliminated [5], as well as teams in which less than 60 % of the members delivered their surveys. In consequence, the final sample includes 86 teams.

2.3 Measures

To obtain *team size*, leaders were asked about the number of elements of their teams. To measure *transformational leadership* we used the *Global Transformational Leadership* (GTL) scale developed by Carless et al. [10] and adapted to the Portuguese language by van Beveren [40]. This scale is composed of seven items (each item measures one of the seven characteristics of transformational leaders in accordance with Carless et al. [10]) that are measured on a 5-point Likert scale from 1 = "almost doesn't apply" to 5 = "almost totally applies". A sample item is "My team leader encourages thinking about problems in new ways and questions assumptions". The Cronbach α for this scale is .96.

To measure *team autonomy* we used the *Team-Level Autonomy scale* (TLA) developed by Langfred [21] and adapted to the Portuguese language by van Beveren [40]. This scale is composed of seven items that are evaluated on a 5-point Likert scale from 1 = "almost doesn't apply" to 5 = "almost totally applies". A sample item is "The team is free to choose the method(s) to use in carrying out work". The Cronbach α for this scale is .90.

To measure *team resilience* a three items scale developed by Stephens et al. [37] and adapted to the Portuguese language by Albuquerque [1] was used. Statements are evaluated on a 5-point Likert scale ranging from 1 = "almost doesn't apply" to 5 = "almost totally applies". A sample item is "Team members know how to handle difficult situations when we face them". The Cronbach α for this scale is .92.

To measure *supportive behaviors* a scale developed by Aubé and Rousseau [2] and adapted to the Portuguese language by Pessoa [28] was used. This scale is composed of 5 items that are measured on a 5-point Likert scale from 1 = "almost doesn't apply" to 5 = "almost totally applies". A sample item is "We help each other out if someone falls behind in his/her work". The Cronbach α for this scale is .93.

To measure *team learning* we used the *Team Learning Behaviors' Instrument* developed by Savelsbergh et al. [36] and adapted to the Portuguese language by Dimas et al. [13]. The Portuguese adaptation is composed of 25 items that are measured on 5-point Likert scales from 1 = "almost doesn't apply" to 5 = "almost totally applies". It has five dimensions, which correspond to the five learning behaviors proposed by Edmondson [15] (exploring and co- construction of meaning, collective reflection, error management, feedback behavior, and experimenting). A sample item is "If something has gone wrong, the team takes the time to think it". The Cronbach αs for the five dimensions of this scale are above .88. In the present study, since the intercorrelations between the five team learning dimensions were very high (between .63 and .84), the presence of a second order factor was tested through a Confirmatory Factor Analysis and, as result, a global score of team learning will be used in the following analyses.

To measure team effectiveness, as explained above, four different criteria were used: team performance, team viability, team process improvement and quality of the group experience. All scales used to measure these variables were developed by Aubé and Rousseau [2] and Rousseau and Aubé [35] and were adapted to the Portuguese language by Albuquerque [1].

Team performance scale is composed of five items that are rated on a 5-point Likert scale from 1 = "very low" to 5 = "very high". A sample item is "Achievement of performance goals". The Cronbach α for this scale is .83.

Quality of the group experience scale is composed of 3 items. Each sentence is measured on 5 point-Likert scales from 1 = "strongly disagree" to 5 = "strongly agree". A sample item is "The social climate in our work team is good". The Cronbach α for this scale is .94.

Team viability scale is composed of four items that are measured on a 5-point Likert scale from 1 = "almost doesn't apply" to 5 = "almost totally applies". A sample item is "The members of this team could work together for a long time". The Cronbach α for this scale is .84.

Finally, *team process improvement* scale is constituted by 5 items rated on 5 point-Likert scales from 1 = "almost doesn't apply" to 5 = "almost totally applies". A sample item is "Team members have successfully implemented new ways of working to facilitate achievement of performance goals". The Cronbach α for this scale is .86.

2.4 RBF Interpolation Models

For any finite data set, radial basis functions (RBFs) can provide excellent interpolants. However, a RBF model may exhibit undesirable trends if the data points are scarce and/or irregularly distributed in a high dimensional space. Therefore, a principal component analysis (PCA) is recommended to detect any collinearity of the attributes of the data points and to transform correlated variables into uncorrelated ones. PCA can also be applied as a data reduction strategy but that is not the goal of this study. Thus, PCA is used here as a structure detection and correction method.

Principal Component Analysis. Given a set of N data points, $\mathbf{p}^1, \ldots, \mathbf{p}^N$, with n components each (in $\mathbb{R}^n$) where $\mathbf{p}_i^j$ represents the ith component of $\mathbf{p}^j$, the PCA is done as follows. First, scale each component by its estimated standard deviation, $\hat{\mathbf{p}}_i^j = \mathbf{p}_i^j/\sigma_i$, where

$$\sigma_i = \frac{1}{N-1}\sqrt{\sum_{j=1}^{N}\left(\mathbf{p}_i^j - \mathrm{ave}(\mathbf{p}_i)\right)^2},$$

with $\mathrm{ave}(\mathbf{p}_i) = \frac{1}{N}\sum_{k=1}^{N}\mathbf{p}_i^k$. Then, compute the covariance matrix $\mathbf{C}$ of the scaled data points $\hat{\mathbf{p}}^1, \ldots, \hat{\mathbf{p}}^N$,

$$\mathbf{C} = \frac{1}{N-1}\sum_{j=1}^{N}\left[\hat{\mathbf{p}}^j - \mathrm{ave}(\hat{\mathbf{p}})\right]\left[\hat{\mathbf{p}}^j - \mathrm{ave}(\hat{\mathbf{p}})\right]^T.$$

The collinearity of the variables can be assessed using the spectral decomposition of $\mathbf{C}$, $\mathbf{C} = \sum_{j=1}^{n}\lambda_j\mathbf{u}^j(\mathbf{u}^j)^T$, where $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n \geq 0$ are the eigenvalues of $\mathbf{C}$, and $\mathbf{u}^1, \ldots, \mathbf{u}^n$ are the corresponding unit eigenvectors. The unit vector $\mathbf{u}^j$ is the jth feature vector of the scaled data set $\hat{\mathbf{p}}^1, \ldots, \hat{\mathbf{p}}^N$ and the scalar $v_j = \hat{\mathbf{p}}^T\mathbf{u}^j$ is the jth principal component of $\hat{\mathbf{p}}$.

The value of each eigenvalue of $\mathbf{C}$, λ_j, indicates the significance the jth principal component of $\hat{\mathbf{p}}$ in representing the variance in the scaled data set.

Thus, the PCA procedure can be seen as an ordination technique for describing the variation in a multivariate data set. The first principal component (first axis) corresponds to the most significant direction of variance in the scaled data set, the second principal component corresponds to the second most significant direction of variance in the principal component, and so forth, with each direction orthogonal to the preceding ones. We can write each data point $\hat{\mathbf{p}}^k$ as a linear combination of the feature vectors $\mathbf{u}^1, \ldots, \mathbf{u}^n$:

$$\hat{\mathbf{p}}^k = \text{ave}(\hat{\mathbf{p}}) + \sum_{j=1}^{n} \left[(\hat{\mathbf{p}}^k - \text{ave}(\hat{\mathbf{p}}))^T \mathbf{u}^j \right] \mathbf{u}^j. \tag{1}$$

By applying PCA to a given set of data points, we can treat the response as a function defined on a feature space, solve the approximation problem by fitting the transformed data in the feature space, and then recover the approximate response in the original input space using Eq. (1). For a more thoroughly description of PCA see, e.g., [22, sect. 3.6].

RBF Interpolation in the Feature Space. Given a set of N data points, $\mathbf{p}^1, \ldots, \mathbf{p}^N$, if the true responses, $f(\mathbf{p}^j)$, $j = 1, \ldots, N$, are known, the goal is to construct a model $g(\mathbf{p})$, using a RBF, $\varphi(x)$, such that $g(\mathbf{p}^j) = f(\mathbf{p}^j), j = 1, \ldots, N$. For the reasons stated above, the RBF interpolant may overfit the data and exhibit undesirable trends between the data points. Thus, using PCA we transform the data fitting problem into a problem in the feature space and find there a RBF interpolant $g(\mathbf{v})$ such that

$$g(\mathbf{v}^j) = f(\mathbf{p}^j), j = 1, \ldots, N, \tag{2}$$

where $\mathbf{v}^j = v_i^j = (\hat{\mathbf{p}}^j - \text{ave}(\hat{\mathbf{p}}))^T \mathbf{u}^i, i = 1, \ldots, n, j = 1, \ldots, N$.

The interpolation model $g(\mathbf{v})$ can be represented as

$$g(\mathbf{v}) = \sum_{j=1}^{N} \alpha_j \varphi(\|\mathbf{v} - \mathbf{v}^j\|), \tag{3}$$

where α_j are the coefficients to be determined by interpolation conditions (2), $\|\mathbf{v} - \mathbf{v}^j\|$ corresponds to the parameterized distance between $\mathbf{v}$ and $\mathbf{v}^j$,

$$||\mathbf{v} - \mathbf{v}^j|| = \sqrt{\sum_{i=1}^{n} |\theta_i| \big(v_i - v_i^j\big)^2}, \tag{4}$$

and $\theta_1, \ldots, \theta_n$ are the model tuning parameters that need to be optimized for obtaining the best prediction model of the given data.

For fixed parameters θ_i, the coefficients $\alpha_1, \ldots, \alpha_N$ in Eq. (3) can be computed by solving the following linear system of interpolation equations:

$$\sum_{j=1}^{N} \alpha_j \varphi(||\mathbf{v}^k - \mathbf{v}^j||) = f(\mathbf{p}^k), \quad \text{for } k = 1, \ldots, N. \tag{5}$$

For multiquadric and Gaussian RBFs, the interpolation matrix of the linear system (5) is nonsingular, provided that all data points are different, which guarantees the existence of a unique interpolant. However, the interpolation matrix of the linear system (5) can be nonsingular for cubic and thin plate spline RBFs. In such case, adding a low-degree polynomial to the interpolation functions in Eq. (3) solves the problem [31].

The most commonly used RBF [31] are multiquadric $\varphi(x) = \sqrt{1 + x^2}$, thin plate spline $\varphi(x) = x^2 \ln x$, cubic spline $\varphi(x) = x^3$, and Gaussian $\varphi(x) = \exp(-\mathrm{x}^2)$. These RBFs can be used to model almost linear, almost quadratic, and cubic growth rates, as well as exponential decay of the response for trend predictions. The constructed interpolant $g(\mathbf{v})$ in Eq. (3) depends on "subjective" choice of $\varphi(x)$, and model parameters $\theta_1, \ldots, \theta_n$. While one can try all the possible choices of $\varphi(x)$ in search of a desirable interpolant, there are infinitely many choices for $\theta_1, \ldots, \theta_n$. Instead, cross-validation is used to determine the optimal value of $\theta_1, \ldots, \theta_n$ that yield an interpolant $g(\mathbf{v})$ with the most accurate trend prediction.

Model Parameter Tuning by Cross-Validation. RBF interpolation models use the parameterized distance of Eq. (4). Model parameter tuning for RBF interpolation consists in obtain a set of parameters $\theta_1, \ldots, \theta_n$ that leads to the best prediction model of the unknown response based on the available data. Other metrics instead of fitting errors must be used to compute the optimal scaling parameters θ_i and determine which basis function $\varphi(x)$ are most appropriate to model the response function $f(\mathbf{p})$, because a RBF interpolant, $g(\mathbf{p})$, exactly fits $f(\mathbf{p})$ for $\mathbf{p} = \mathbf{p}^k, k = 1, \ldots, N$. Cross-validation (CV) [38] was proposed to find $\varphi(x)$ and θ_i that lead to an approximate response model $g(\mathbf{p})$ with optimal prediction capability [31]. The leave-one-out CV procedure is usually used in model parameter tuning for RBF interpolation (see [31]).

Leave-One-Out Cross-Validation for RBF Interpolation:

- Fix a set of parameters $\theta_1, \ldots, \theta_n$.
- For $j = 1, \ldots, N$, construct the RBF interpolant $g_{-j}(\mathbf{p})$ of the data points $(\mathbf{p}^k, f(\mathbf{p}^k))$ for $1 \leq k \leq N, k \neq j$.
- Use the following CV root mean square error as the prediction error:

$$E^{CV}(\theta_1, \ldots, \theta_n) = \sqrt{\frac{1}{N} \sum_{j=1}^{N} (g_{-j}(\mathbf{p}^j) - f(\mathbf{p}^j))^2}. \tag{6}$$

The goal of model parameter tuning by CV is to minimize the CV error $E^{CV}(\theta_1, \ldots, \theta_n)$ by finding optimal $\theta_1, \ldots, \theta_n$ so that the interpolation model has the highest prediction accuracy when CV error is the measure. It should be highlighted that, most of the time, this optimization problem is very difficult as the $E^{CV}(\theta_1, \ldots, \theta_n)$ function is highly nonlinear and nonconvex [30]. A straightforward simplification of this problem is to consider $\theta_1 = \cdots = \theta_n$, which reduces the problem to a simple unconstrained minimization of a univariate function. Despite the fact that this simplification has the benefit of dealing with a simple unidimensional optimization problem, it has the disadvantage of not using all different θ_i which allows the model parameter tuning to scale each variable p_i based on its significance in modeling the variance in the response. Thus, considering all θ_i different have the benefit of implicit variable screening built in the model parameter tuning.

3 Results

In this study, the unit of analysis was the group rather than the individual and, as a result, members' responses were aggregated to the team level. To examine whether the data justified aggregation the Average Deviation Index (AD_M Index) developed by Burke, Finkelstein, and Dusig [9] was performed. Following the authors' recommendations, we used the criterion $AD_M \leq 0.83$ to aggregate, with confidence, individual responses to the team level. The average AD_M values obtained for each variable were below the upper-limit criterion of 0.83 revealing that the level of within-team agreement was sufficient to aggregate team members' scores.

A correlation analysis was performed to assure that the variables to include in the models are correlated with the outcome. Significant and negative correlation was found between effectiveness and team size while correlations found between effectiveness and the remaining variables were significant and positive. Supportive behaviors presented the strongest correlation between variables and outcome ($r = .622, p < .01$). The correlation between variables is significant and positive except for team size that has a significant and negative correlation with the remaining variables (Table 1).

MATLAB code *fminsearch*, an implementation of the Nelder-Mead [26] multidimensional search algorithm, was used to minimize the CV error in Eq. (6) and to find the best model parameters $\theta_1, \ldots, \theta_n$. The local optimal solution generated by MATLAB code *fminsearch* for minimization of the CV error is very reliable but also very sensitive to the initial guess. Multiple initial guesses were used for searching a global minimizer of the CV error by *fminsearch*.

The CV error of a constructed approximation can be used as an objective tool to help analysts on the difficult task of deciding which RBF model is better for the problem at hand. Table 2 displays the CV errors of the various RBF interpolation models considering different basis functions. The approximation model that, among all the approximation models, better capture the information "buried" in the data set usually corresponds to the smallest value of minimized CV errors [31]. By simple inspection of Table 2 we can verify that multiquadric RBF lead to the model with smallest CV error. Thus, multiquadric RBF model was selected to study the relationship between the variables and the outcome.

Table 1. Correlation analysis.

	Effectiveness	Team size	Leadership	Learning	Resilience	Supportive behaviors	Autonomy
Effectiveness	1	$-.276^{*}$	$.492^{**}$	$.558^{**}$	$.525^{**}$	$.622^{**}$	$.445^{**}$
Team size		1	$-.309^{**}$	$-.436^{**}$	$-.297^{**}$	$-.367^{**}$	$-.276^{*}$
Leadership			1	$.784^{**}$	$.596^{**}$	$.678^{**}$	$.557^{**}$
Learning				1	$.676^{**}$	$.709^{**}$	$.691^{**}$
Resilience					1	$.769^{**}$	$.496^{**}$
Supportive behaviors						1	$.555^{**}$
Autonomy							1

Note: ** $p < .01$; * $p < .05$.

Table 2. Optimal CV errors for the data set.

Multiquadric CV error	Thin plate CV error	Cubic CV error	Gaussian CV error
0.78	1.13	1.57	1.28

Figure 1 display the relationships between effectiveness and each of the six variables considered. Data points were added to the plots to give an indication of the scatter in the data. The baseline data point, i.e. the data point for which the remaining variables are kept constant is also plotted for perspective. In order to benchmark the multiquadric RBF model results, the following multiple linear regression model, obtained using SPSS, was also added:

$$\begin{aligned}\text{Effectiveness} = {} & 1.84 + 0.00 \times (\text{Team size}) + 0.00 \times (\text{Leadership}) \\ & + 0.15 \times (\text{Learning}) + 0.04 \times (\text{Resilience}) \\ & + 0.34 \times (\text{Supportive behaviors}) + 0.04 \times (\text{Autonomy}).\end{aligned}$$

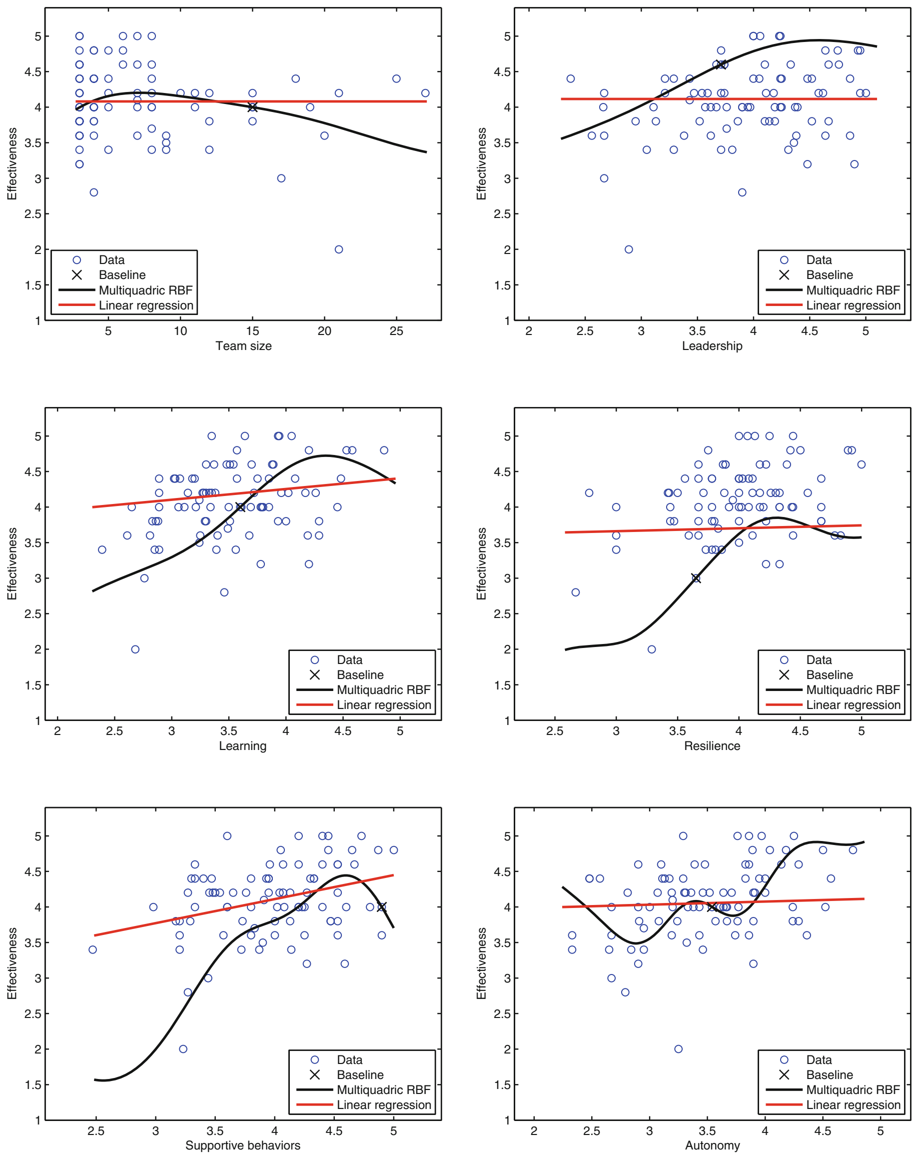

Fig. 1. Two-dimensional plots of linear and multiquadric RBF models.

4 Discussion and Conclusions

In general, the results obtained are quite satisfactory. The trends found by the multiquadric RBF model concerning the relationships between the team resources/processes and team effectiveness are promising. Indeed, the nature of the results found put forward the need to consider methodologies beyond the linear widespread approach to better capture the complexity of team functioning.

The first result to discuss concerns the relationship between team size and team effectiveness. Literature on groups has shown that team size is a key variable influencing group dynamics and performance. As the size of a team increases, so does the quantity of resources available, but also the need for coordination [29]. In this way, the questions concerning the "optimal" team size are complex and are yet to be fully answered [20]. In fact, whereas some studies suggest that smaller size is better [42], other studies show that increasing team size improves performance [11]. The present study, through a nonlinear approach, and with a large sample composed of different types of organizational teams, gives a contribution to this debate. Hence, our results, which are in line with Nieva, Fleishman and Reick [27], show that the relationship between team size and team effectiveness is nonlinear: teams with five to ten members outperform smaller teams, where resources are lacking, and also larger teams, where coordination becomes difficult.

Concerning transformational leadership, team learning, team resilience, supportive behaviors and team autonomy, nonlinear patterns are also shown. Increasing trends up to a certain threshold are displayed, followed by a deflation for the highest values of the respective variables. Hence, our results show that more is not always better, suggesting that at higher values of the variables considered an inversion is reached, opposing to linear results. These results are in line with those of Bunderson and Sutcliffe [8] on the relationship between team learning and performance. The authors found that too much emphasis on learning can compromise efficiency because detract the team from results, and this is particular salient for teams that have been performing well. The present study extends those results by showing that this pattern is identified not only when performance is considered but also when a more embracing conception of effectiveness is adopted (that integrates four criteria). Moreover, our results highlight that this trend is identified also with other variables important for team functioning. A comprehensive explanation can be presented about the nature of the relationships between transformational leadership, team resilience, supportive behaviors with team effectiveness: when team members gives too much instrumental and emotional support to other members, time is consumed without assurance of results, and that might therefore reduce effectiveness; leaders that present too much transformational leadership behaviors might be to active in stimulating the team to develop, interfering excessively with team functioning and, then, effectiveness might suffers [6]; and finally, too much team resilience could lead to overconfidence, increasing the chance of committing errors and thus affecting effectiveness [41].

It is worth to highlight that, apart from team autonomy, all remaining variables do not present minor trend changes (oscillations). Despite the oscillations displayed for smaller values of team autonomy, the overall trend is similar to the remaining variables. By combining principal component analysis, RBF interpolation, and cross-validation for model parameter tuning, we obtain a data fitting method that generates an approximate response with more desirable trend predictions between the given data points, less likely to overfit the data, i.e. to display unreliable minor trend changes that might lead to undesirable characteristics such as oscillations.

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