IMPROVING SCRUM-MANAGED PROJECT PLANNING THROUGH PRODUCTIVITY ANALYSIS

01-003

IMPROVING SCRUM-MANAGED PROJECT PLANNING THROUGH PRODUCTIVITY ANALYSIS

Ottaviani, Filippo Maria [(1)]; Ballesteros-Pérez, Pablo [(2)]; Mora-Meliá, Daniel [(2)]; De Marco, Alberto [(1)]

[(1)] Politecnico di Torino, [(2)] Universitat Politècnica de València

In projects managed under the SCRUM framework, planning involves estimating the time and effort required to complete the user stories and optimizing the resources' workload. Hence, it is necessary to assess not only the affinity between user stories and those of completed projects but also the deviations in productivity through the project sprints. However, balancing the estimated SCRUM team workload across multiple projects is generally difficult. This study proposes a planning and monitoring tool for projects managed with SCRUM: the SCRUM productivity curve. This productivity curve is calculated by comparing the planned and actual amounts of person-hours from planned and completed user stories. To achieve this, we employ non-linear regression comparing actual productivity data with a theoretical model. The most relevant calculations are developed using a real case study implementing the SCRUM framework. It shows how the proposed SCRUM productivity curve can help project managers balance the resource workload at the project and portfolio levels.

Keywords: SCRUM; project planning; productivity analysis

MEJORA DE LA PLANIFICACIÓN DE PROYECTOS GESTIONADOS POR SCRUM MEDIANTE EL ANÁLISIS DE LA PRODUCTIVIDAD

En los proyectos gestionados según el marco SCRUM, la planificación implica estimar el tiempo y el esfuerzo necesarios para completar las historias de usuario y optimizar la carga de trabajo de los recursos. Por lo tanto, es necesario evaluar no sólo la afinidad entre las historias de usuario y las de los proyectos completados, sino también las desviaciones en la productividad a través de los sprints del proyecto. Sin embargo, equilibrar la carga de trabajo estimada del equipo SCRUM en varios proyectos suele ser difícil. Este estudio propone una herramienta de planificación y seguimiento de proyectos gestionados con SCRUM: la curva de productividad SCRUM. Esta curva de productividad se calcula comparando las cantidades planificadas y reales de horas-persona de las historias de usuario planificadas y completadas. Para ello, se emplea una regresión no lineal que compara los datos reales de productividad con un modelo teórico. Los cálculos más relevantes son aplicados utilizando un caso de estudio real que implementa el marco SCRUM. En dicho caso se demuestra cómo la curva de productividad SCRUM propuesta puede ayudar a los gerentes de proyectos a equilibrar la carga de trabajo de los recursos a tanto nivel de proyecto y de portafolio.

Palabras clave: SCRUM; planificación de proyectos; análisis de productividad

CONTENT

1. Introduction

Program management is crucial to achieving strategic business objectives that individual projects cannot accomplish alone (PMI, 2017). A key aspect of program management is optimizing shared resources among multiple projects, which is critical in maximizing their effectiveness and efficiency (Lycett et al., 2004). This step is particularly important in programs which projects are managed with an agile approach, as resources, unlike in the waterfall methodology, are not variables to be estimated but actual project constraints (Hoda & Murugesan, 2016).

Agile project management has gained significant popularity in both academic and industrial domains for its capability to offer flexibility, adaptability, and responsiveness to changing project requirements (Chagas et al., 2014). Among the many agile practices, SCRUM is one of the most used frameworks (Hron & Obwegeser, 2022). Developed by Ken Schwaber and Jeff Sutherland in the early 1990s (Schwaber, 2023), SCRUM is designed to help teams deliver products faster, with greater collaboration and customer satisfaction, by emphasizing transparency, self-organization, and continuous improvement. Initially employed in the IT sector, the framework has demonstrated its success in various industries (Azanha et al., 2017; Paasivaara et al., 2008; Pries-Heje & Pries-Heje, 2011; Sutherland & Schwaber, 2011).

In SCRUM, resources hold a central position as several ceremonies revolve around them, enabling teams to respond quickly to changing requirements and deliver better customer results (Bass, 2014). While resources' estimation of expected time and cost for project activities is vital, the framework does not account for any qualitative, human factor-related, or environmental variables that may affect their performance (de O. Melo et al., 2013; Sutherland, 2005). The cost and duration of activities are determined during sprint planning (Schwaber, 2004). Activity cost is usually expressed in story points, which reflect the effort required to complete an activity (Wautelet et al., 2014). Instead, the duration is estimated based on the team's capacity for the next sprint. Nevertheless, estimates can be changed as the team acquires more information or as updated data becomes available (Zahraoui & Janati Idrissi, 2015).

The primary purpose of sprint estimates is to provide a basis for planning and assist the team in managing its workload effectively rather than offering an accurate forecast of activity cost and duration. As the team works on activities during the sprint, they can revise the estimates and update the sprint backlog accordingly. However, it is possible to anticipate productivity changes without deciding from sprint to sprint. There are two possible approaches to achieve this. The first method identifies project phases and assesses the effort required accordingly (Putnam, 1978; Warburton, 1983). The second approach entails analyzing resource learning curves throughout project execution, which can change throughout the sprints (Albero Pomar et al., 2014; Al-Sabbagh & Gren, 2018; Gren & Al-Sabbagh, 2017).

2. Objectives

This study presents a framework for analyzing resource performance in projects managed using the SCRUM methodology. In particular, the proposed framework outlines the steps for evaluating resource productivity, which can be to predict estimated progress or balance resource workloads for future initiatives. Resource productivity is measured by the number of person-hours required to complete user stories based on the project phase. Nonlinear regression is used to fit the recorded data into a theoretical model. The framework is applied to a real case study to guide practitioners in its application.

3. SCRUM Planning Process

The planning process in SCRUM is similar to that of the waterfall methodology, comprising two phases: the first phase identifies the work to be done, while the second phase determines the time and cost involved (*A Guide to the Scrum Body of Knowledge*, 2016). In the first phase, decomposes the project scope into initiatives, epics, and user stories (Atlassian, 2023), whose relationships are as follows. A project comprises different initiatives, which are high-level goals or objectives that the product owner wants to achieve for the project. Each initiative is broken down into epics and user stories to make them more manageable and easier to prioritize. Epics are large user stories that cannot be completed in a single sprint and, for this reason, are further broken down into smaller, more manageable user stories. User stories are small, self-contained units of work that represent a single piece of functionality from the user's perspective. User stories are completed within a single sprint, driving the development process forward.

The second phase of the planning project involves evaluating the project's time and cost by assessing the user stories using time-based estimates (in hours) or relative estimates (in story points). The development team conducts the estimation process during sprint planning, which includes reviewing the user story, breaking it into multiple tasks, estimating each task's requirements, assigning estimates to the user story, and validating the estimates. The output of the preliminary estimate step is the user stories timeline, which determines how many user stories should be completed within each sprint and how many resources, i.e., effort, are required to complete them.

4. Research Methods

The proposed framework consists of four steps: preliminary estimation, assessment of actual values, nonlinear regression, and adjustment of estimates.

Let t indicate the tth sprint: while $t = 1$ indicates the project beginning, $t = \mathrm{PD}$ indicates the project planned duration; therefore, $t \in [1..\mathrm{PD}]$. Let $dUS(t)$ indicate the user stories completed in the tth sprint, and US^{tot} indicate the total number of user stories in the project, so that Equation 1 subsists.

$$US^{\mathrm{tot}} = \sum_{t=1}^{\mathrm{PD}} dUS(t) \quad (1)$$

Following the SCRUM methodology, each sprint lasts the same number of workdays, wd, and each workday involves the same number of working hours, wh. Let $R(t)$ indicate the number of resources allocated to the tth sprint. If each resource works a maximum of wh hours per workday, then the effort spent per sprint, $dE(t)$, is evaluated as per Equation 2.

$$dE(t) = R(t) \cdot wh \cdot wd \qquad (2)$$

The total effort, E^{tot}, is given by the sum of the effort spent throughout all sprints, as per Equation 3.

$$E^{\text{tot}} = \sum_{t=1}^{\text{PD}} dE(t) \qquad (3)$$

The sprint productivity, $P(t)$, is given by the ratio of the number of user stories completed in a sprint, $dUS(t)$, to the effort spent in that sprint, $dE(t)$, as per Equation 4.

$$P(t) = dUS(t)/dE(t) \quad (4)$$

4.1 Preliminary Estimation

The preliminary estimation step coincides with the standard scheduling of user stories as per the adopted methodology, i.e., how many user stories are planned to be completed within each sprint, and how many resources are allocated. The planned variables are referred to using the subscript p – i.e., $dUS_p(t)$, $R_p(t)$, $dE_p(t)$, $P_p(t)$.

4.2 Assessment of Actual Values

Assessing the actual values consists of determining the actual progress achieved throughout the sprints, considering the actual effort spent by the resources. The actual variables are referred to using the subscript a – i.e., $dUS_a(t)$, $R_a(t)$, $dE_a(t)$, $P_a(t)$. Comparing the actual number of user stories completed in a sprint, $dUS_a(t)$, with the actual effort spent, $dE_a(t) = R_a(t) \cdot 8 \cdot 10$, allows to determine the actual productivity in that sprint, $P_a(t) = dUS_a(t)/dE_a(t)$.

The ratio of the actual productivity to the planned one provides the relative productivity, $RP(t)$, as per Equation 5.

$$RP(t) = P_a(t)/P_p(t) \quad (5)$$

If $RP(t) = 1$, the actual and planned productivity are equal. Instead, if $RP(t) > 1$, the actual number of user stories completed per unit of effort is greater than the planned one; the opposite applies in the case of $RP(t) < 1$. It should be noted that any of the three situations could hold true due to the proportional reduction/increase of resources and user stories. For example, let $dUS_p(t) = 5$ and $R_p(t) = 5$ then $P_p(t) = 1$. Then, let $dUS_a(t) = 10$ and $R_a(t) = 10$, so that $P_a(t) = 1$. In this case, $RP(t) = P_a(t)/P_p(t) = 1/1$ even though $dUS_a(t) > dUS_p(t)$.

4.3 Nonlinear Regression

Nonlinear regression is a statistical technique that allows to infer the nonlinear relationship, f, between a target variable, y, and a set of independent variables, X, so that $y = f(X) + \epsilon$ where ϵ is the random additive error (Everitt & Skrondal, 2010). The f function is determined by the modeler, while its parameters can be evaluated through the curve fitting procedure, as follows.

Let $\hat{y}$ indicate the prediction. The curve fitting procedure consists of an optimization model, where the objective function is given by Equation 6,

$$\text{minimize } \sum_{t=0}^{\text{PD}} |\hat{y}(t) - y(t)| \quad (6)$$

subject to the constraint presented in Equation 7,

$$\hat{y} = \hat{f}(X) \quad \forall t \in [0..\text{PD}] \quad (7)$$

In this context, the target variable, y, is set to the relative productivity, $RP(t)$, while the independent variables, X, consist of the only tth sprint. The fitted variables are referred to using the subscript f – i.e., $dUS_f(t)$, $R_f(t)$, $dE_f(t)$, $P_f(t)$.

4.4 Estimates Adjustment

The estimates adjustment step consists of using the fitted relative productivity, $R_f(t)$, to adjust the project schedule. Specifically, two methods can be adopted. In the first method, A, the resources allocated follow the baseline schedule, $R_f^A(t) = R_p(t)$, while the forecasted user stories, $dUS_f^A(t)$, depend on the estimated productivity, $P_f(t)$, as per Equation 8.

$$dUS_f^A(t) = P_f(t) \cdot dE_f^A(t) = P_f(t) \cdot R_f^A(t) \cdot wd \cdot wh = RP_f(t) \cdot P_p(t) \cdot R_p(t) \cdot wd \cdot wh \quad (8)$$

In the second method, the user stories to be completed respect the baseline schedule, $dUS_f^B(t) = dUS_p(t)$, while the number of resourced allocated, $R_f^B(t)$, is changed according to the fitted productivity, $P_f(t)$, as per Equation 9.

$$R_f^B(t) = \frac{1}{wd \cdot wh} dE_f^B(t) = \frac{1}{wd \cdot wh} \frac{dUS_f^A(t)}{P_f(t)} = \frac{1}{wd \cdot wh} \frac{dUS_p^A(t)}{RP_f(t) \cdot P_p(t)} \quad (9)$$

5. Application

The following section illustrates the application of the proposed methodology to a real project managed through the SCRUM framework. Specifically, the project consisted of the development of an IT application by a medium-size engineering and consulting company. The resources involved in the project had the same background but had not collaborated before, although each had participated in projects with similar deliverables.

5.1 Preliminary Estimation

The total number of user stories, US^{tot}, was estimated to be 281, distributed linearly over 11 sprints ($\text{PD} = 11$), which provided 25.5 user stories per sprint circa – $dUS(t) \sim 25.5 \ \ \forall\, t \in [1..\text{PD}]$. Each sprint had a duration of ten workdays ($wd = 10$), and each workday consisted of eight workhours ($wh = 8$). The number of resources allocated to each sprint, $R_p(t)$, changed between sprints, with more resources allocated to the earlier phases than to the later ones. The planned effort per sprint, $dE_p(t)$, is computed through Equation 2, while the planned productivity, $P_p(t)$, is computed through Equation 4.

5.2 Assessment of Actual Values

Throughout the project execution, the SCRUM team monitored the actual user stories completed during each sprint, $dUS_a(t)$. This allows to evaluate the actual productivity, $P_a(t)$, and relate it to the planned one, $P_p(t)$, to determine the relative productivity, $RP_a(t)$, through Equation 5. The actual number of resources allocated, $R_a(t)$, respected the planned one,

$R_p(t)$, so the actual effort was equal to the planned one as well – i.e., $dE_p(t) = dE_a(t) \;\; \forall t \in [1..\mathrm{PD}]$.

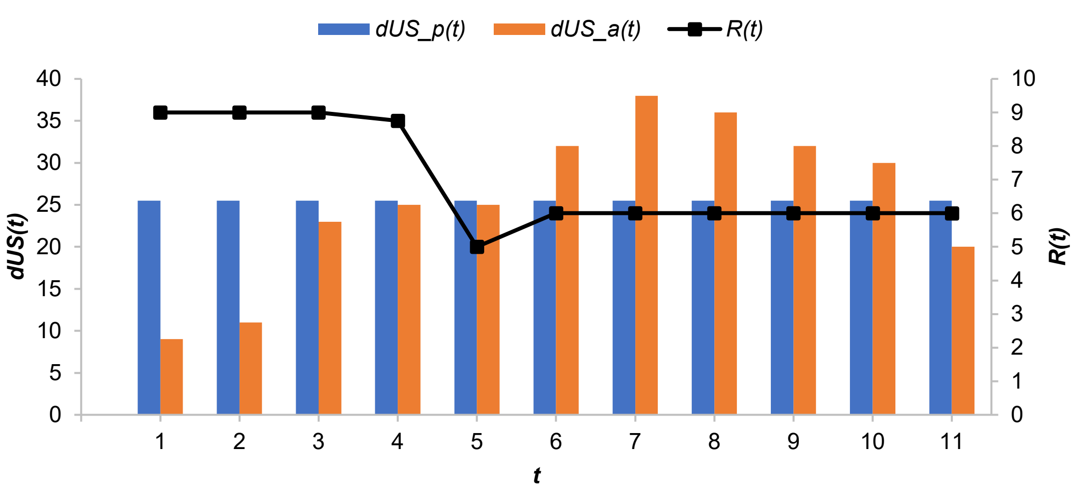
The project planned and actual variables are summarized in Table 1. The last row, where available, indicates the total number of the respective variable.

Table 1. Planned and actual observations

t	Planned				Actual				
	dUS_p	R_p	dE_p	P_p	dUS_a	R_a	dE_a	P_a	RP_a
1	25.5	9	720	3.55E-02	9	9	720	1.25E-02	35%
2	25.5	9	720	3.55E-02	11	9	720	1.53E-02	43%
3	25.5	9	720	3.55E-02	23	9	720	3.19E-02	90%
4	25.5	9	700	3.65E-02	25	9	700	3.57E-02	98%
5	25.5	5	400	6.39E-02	25	5	400	6.25E-02	98%
6	25.5	6	480	5.32E-02	32	6	480	6.67E-02	125%
7	25.5	6	480	5.32E-02	38	6	480	7.92E-02	149%
8	25.5	6	480	5.32E-02	36	6	480	7.50E-02	141%
9	25.5	6	480	5.32E-02	32	6	480	6.67E-02	125%
10	25.5	6	480	5.32E-02	30	6	480	6.25E-02	117%
11	25.5	6	480	5.32E-02	20	6	480	4.17E-02	78%
	281		6140		281		6140		

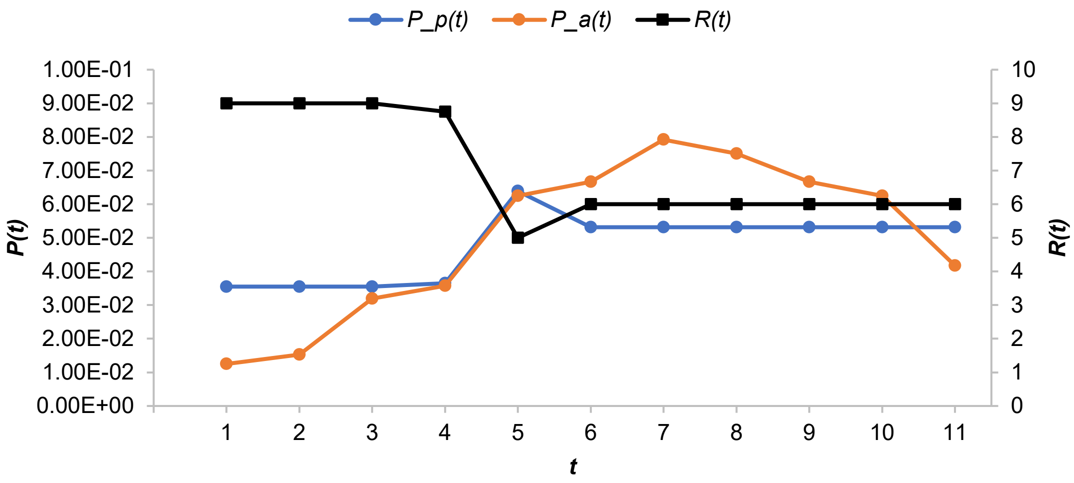
The planned and actual user stories completed per sprint, and allocated resources, are presented in Figure 1. Despite the linear distribution of work over the sprints and allocating more resources during the early sprints, the actual user stories completed follow a nonlinear trend, with peaks during the second half of the sprints.

Figure 1: Comparison of Planned and Actual User Stories Completed



This is further confirmed by comparing the planned and actual productivity, as shown in Figure 2. The planned productivity, $P_p(t)$, increases as the number of resources, $R(t)$, decreases. Instead, the actual productivity, $P_a(t)$, shows a similar trend to the actual user stories, $dUS_a(t)$.

Figure 2: Comparison of Planned and Actual Productivity



5.3 Nonlinear Regression

Nonlinear regression analysis is performed by setting the dependent one to the relative productivity – i.e., $y = RP_a(t)$. Given the relative productivity values from Table 1, $RP_a(t)$, which follow a right-skewed distribution, the Beta distribution is adopted as the theoretical model, f. The probability density function of the Beta distribution is provided by Equation 10,

$$f(x; \alpha, \beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)} \qquad (10)$$

where x is the independent variable, α and β are the distribution shape parameters, and B is the Beta function (Evans et al., 2000). Since the Beta distribution is limited to the interval $0 \leq x \leq 1$, the x variable must be normalized to one. This can be done by setting to the ratio of the tth time unit to the planned duration, PD, so that $0 \leq t/\mathrm{PD} \leq 1$ (Narbaev & De Marco, 2014).

To further improve the accuracy of the nonlinear regression with the Beta distribution, which equals zero at both 0 and t/PD, it is possible to perform the following adjustments (Duncan et al., 2013). Firstly, two additional observations can be added to the dataset. In both, the relative productivity is equal to zero, but one occurs right before the project start, $t = 0$, while the other one occurs after the project end, $t = \mathrm{PD} + 1$. Secondly, the x variable should be rescaled to 1 so that $t/(\mathrm{PD} + 1) = 1$. By doing so, the curve fitting procedure would provide better the data to the Beta distribution. The added observations are provided in Table 2.

Table 2. Added observations

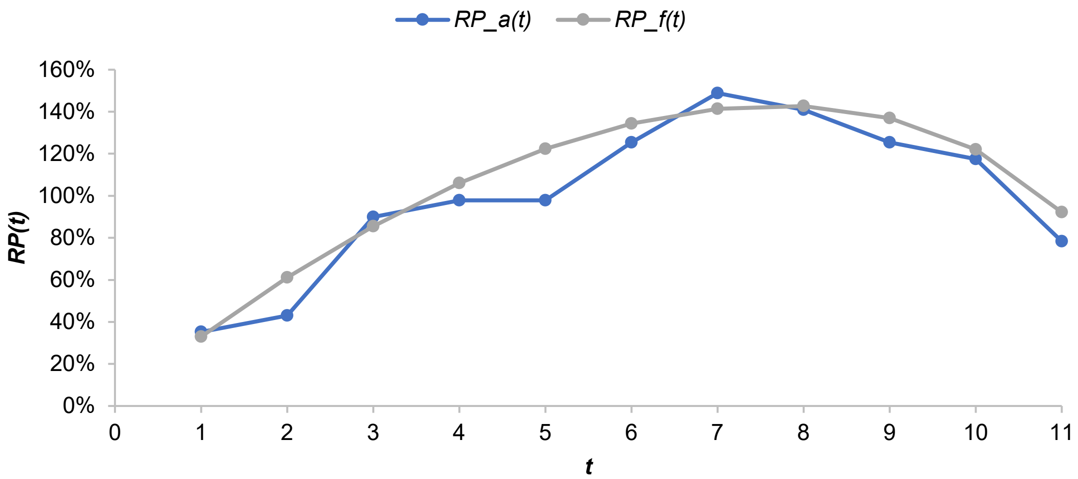
t	$t/(\mathrm{PD}+1)$	Planned				Actual				
		dUS_p	R_p	dE_p	P_p	dUS_a	R_a	dE_a	P_a	RP_a
0	0	0	0	0	0	0	0	0	0	0%
$\mathrm{PD}+1$	1	0	0	0	0	0	0	0	0	0%

Calling the curve fitting procedure (any statistical software is sound) allows to estimate the shape parameters $\alpha \sim 1.97$ and $\beta \sim 1.54$, leading to Equation 11.

$$\widehat{RP}(t) = f(t/\mathrm{PD}; 1.97, 1.54) \qquad (11)$$

the relative productivity is fit to the t values from Table 1. A graphical comparison of the actual and fitted relative productivity curves is provided in Figure 3.

Figure 3: Comparison of Actual and Fitted Relative Productivity



5.4 Estimates Adjustment

The fitted Beta distribution, Equation 11, is used to fit the relative productivity, $RP_f(t)$, throughout the 11 sprints. Then, the two methods illustrated in Section 4.4 are adopted by applying Equations 8 and 9, respectively.

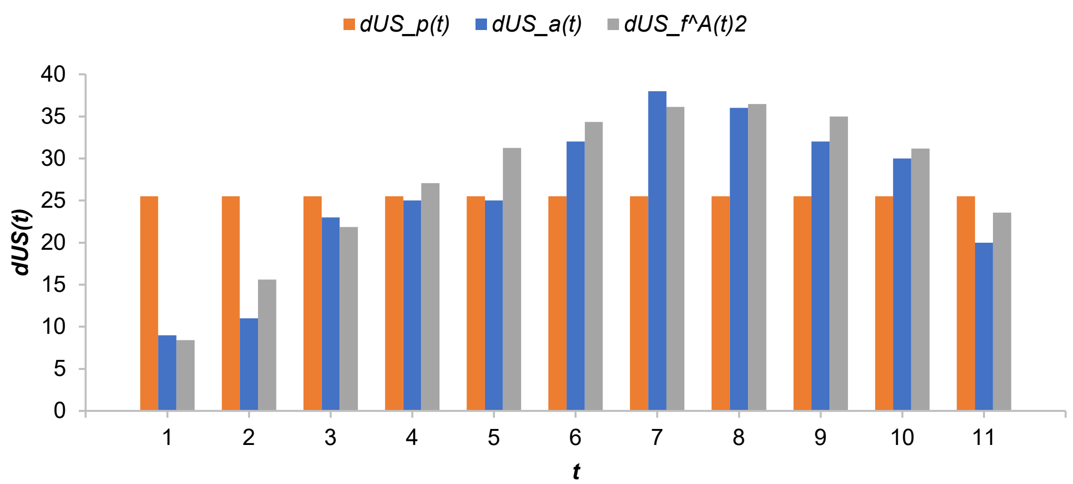
The actual relative productivity and all fitted variables are presented in Table 3. It should be noted that, in method B, the total effort is greater than the planned one (7488 vs 6140). This is due to allocating more resources during the early phases, during which the productivity, is expected to be lower, to complete the planned amount of user stories, $dUS_f^B = dUS_p$.

Table 3. Fitted Variables according to Method Adopted

t	RP_f	$P_f(t)$	Method A			Method B		
			dE_f^A	$R_f^A = R_p$	dUS_f^A	$dUS_f^B = dUS_p$	dE_f^B	R_f^B
1	33%	1.17E-02	720	9.00	8.42	25.55	2186	27.3
2	61%	2.17E-02	720	9.00	15.62	25.55	1177	14.7
3	86%	3.04E-02	720	9.00	21.84	25.55	842	10.5
4	106%	3.87E-02	700	8.75	27.08	25.55	660	8.3
5	122%	7.82E-02	400	5.00	31.27	25.55	327	4.1
6	134%	7.15E-02	480	6.00	34.32	25.55	357	4.5
7	141%	7.52E-02	480	6.00	36.12	25.55	339	4.2
8	143%	7.59E-02	480	6.00	36.45	25.55	336	4.2
9	137%	7.29E-02	480	6.00	35.00	25.55	350	4.4
10	122%	6.49E-02	480	6.00	31.16	25.55	393	4.9
11	92%	4.90E-02	480	6.00	23.54	25.55	521	6.5
			6140		281	281	7488	

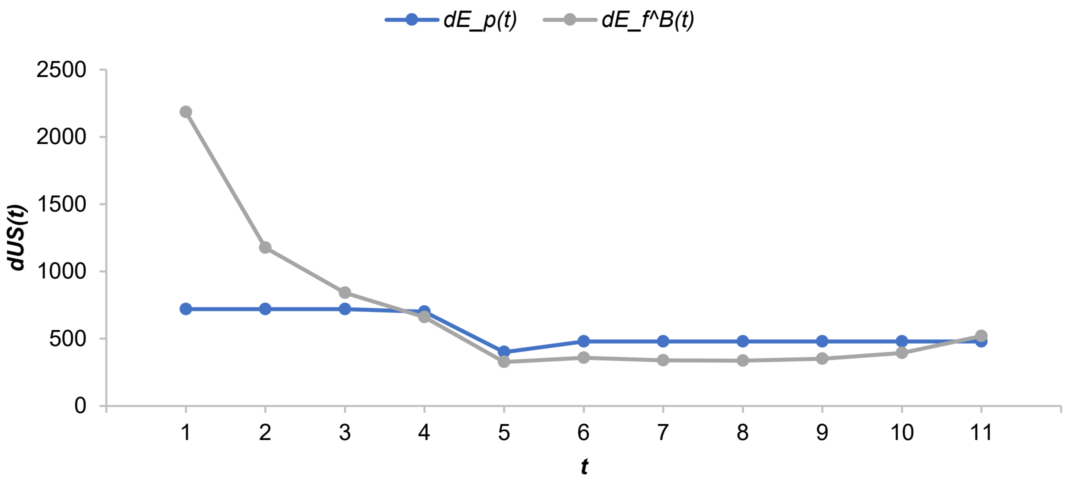
Following method A, the accuracy of the relative productivity fit compared to the actual one would provide an accurate forecast of the user stories completed, as shown in Figure 4.

Figure 4: Comparison of Planned, Actual, and Fitted User Stories



On the other hand, following method B would determine a different balancing of the SCRUM team, with significantly more effort allocated to the early stages of the project, as shown in Figure 5.

Figure 5: Comparison of Actual and Fitted Relative Productivity



6. Discussions

Previous research in the area of planning and monitoring within the SCRUM framework has primarily examined the productivity of resources in a qualitative manner or through empirical observation of differences, yet without offering any prescriptive guidance. The present study aims to contribute to this gap by proposing a framework for modeling the learning curve of SCRUM teams. This framework provides valuable information that can be used to estimate the completion of user stories, as well as adjust resource allocation to align with the original schedule. By offering such practical guidance, this study has the potential to enhance the effectiveness of SCRUM project management.

The findings of this study are supported by Table 1, Figure 1, and Table 2, which demonstrate that although the user stories were distributed linearly across the sprints, resource productivity exhibited a rising trend, resulting in the team completing the project on schedule. To refine our analysis, we preprocessed the monitoring data, which allowed us to better estimate the parameters of the theoretical model adopted (i.e., the Beta distribution) through nonlinear regression analysis. The accuracy of the fitted relative productivity was evaluated in Figure 3, demonstrating its ability to capture the first rising and then declining trend of actual productivity. As a result, two methods were proposed for forecasting user stories: method A forecasts the user stories the team anticipates completing in the sprints, while method B calculates the expected effort required to complete the planned user stories. A comparison of the fitted and planned variables is provided in Table 3, as well as Figures 4 and 5. These results provide valuable insights into SCRUM project management, highlighting the importance of monitoring and forecasting resource productivity to ensure timely project completion.

7. Conclusions

Agile project management has gained significant traction in managing complex projects, owing to its effective modularization of work. Of these methodologies, the SCRUM framework has emerged as one of the most widely adopted due to its focus on resource allocation and utilization in project implementation. However, while the literature has seen notable advancements in recent years, the quantitative analysis of the learning curve of resources, and the resulting productivity observed during project sprints, has received scant attention. Such quantitative insights are crucial in analyzing project performance, and facilitating program-level decisions related to progress forecasting and resource allocation. Thus, there is a pressing need to further explore and understand the learning curve of resources in SCRUM project management.

This study presents a comprehensive framework for assessing resource productivity in SCRUM-managed projects. The framework comprises four distinct phases. In the first phase, preliminary planning is conducted to estimate the user stories to be completed during each sprint and allocate corresponding resources and effort. The second phase involves evaluating current variables to determine the actual productivity of resources and quantify their relative productivity. The third stage entails employing nonlinear regression analysis to develop a theoretical model that accurately describes the observed relative productivity function. The fourth and final phase consists of two methods: Method A employs the fitted relative productivity curve to forecast the number of user stories that can be completed with the allocated resources, while Method B uses the same curve to estimate the effort required to complete the planned user stories.

The study provides an illustrative application of the framework to a real project. The results highlight how the relative productivity shown by the SCRUM team is nonlinear, increasing, and how it can be modeled to improve the project planning and monitoring process. Future research directions consist in extending the analysis to a dataset of projects with different resources but similar deliverables to outline a model not only for retrospective analysis, but to be used in new initiatives.

REFERENCES

A Guide to the Scrum Body of Knowledge. (2016). SCRUMstudy™.

Albero Pomar, F., Calvo-Manzano, J. A., Caballero, E., & Arcilla-Cobián, M. (2014). Understanding sprint velocity fluctuations for improved project plans with Scrum: a case study. *Journal of Software: Evolution and Process*, *26*(9), 776–783. https://doi.org/10.1002/smr.1661

Al-Sabbagh, K. W., & Gren, L. (2018). The connections between group maturity, software development velocity, and planning effectiveness. *Journal of Software: Evolution and Process*, *30*(1), e1896. https://doi.org/10.1002/smr.1896

Atlassian. (2023). *Stories, epics, and initiatives*. https://www.atlassian.com/agile/project-management/epics-stories-themes

Azanha, A., Argoud, A. R. T. T., de Camargo Junior, J. B., & Antoniolli, P. D. (2017). Agile project management with Scrum: A case study of a Brazilian pharmaceutical company IT project. *International Journal of Managing Projects in Business*, *10*(1), 121–142. https://doi.org/10.1108/IJMPB-06-2016-0054

Bass, J. M. (2014). Scrum Master Activities: Process Tailoring in Large Enterprise Projects. *2014 IEEE 9th International Conference on Global Software Engineering*, 6–15. https://doi.org/10.1109/ICGSE.2014.24

Chagas, L. F., de Carvalho, D. D., Lima, A. M., & Reis, C. A. L. (2014). Systematic Literature Review on the Characteristics of Agile Project Management in the Context of Maturity Models. In *CCIS* (Vol. 477, pp. 177–189). https://doi.org/10.1007/978-3-319-13036-1_16

de O. Melo, C., S. Cruzes, D., Kon, F., & Conradi, R. (2013). Interpretative case studies on agile team productivity and management. *Information and Software Technology*, *55*(2), 412–427. https://doi.org/10.1016/j.infsof.2012.09.004

Evans, M., Hastings, N., & Peacock, B. (2000). Beta distribution. In *Statistical distributions* (3rd ed., pp. 34–42). Wiley-Interscience.

Everitt, B. S., & Skrondal, A. (2010). *The Cambridge Dictionary of Statistics*. Cambridge University Press. https://doi.org/10.1017/CBO9780511779633

Gren, L., & Al-Sabbagh, K. (2017). Group Developmental Psychology and Software Development Performance. *2017 IEEE/ACM 39th International Conference on*

Software Engineering Companion (ICSE-C), 232–234. https://doi.org/10.1109/ICSE-C.2017.85

Hoda, R., & Murugesan, L. K. (2016). Multi-level agile project management challenges: A self-organizing team perspective. *Journal of Systems and Software*, *117*, 245–257. https://doi.org/10.1016/j.jss.2016.02.049

Hron, M., & Obwegeser, N. (2022). Why and how is Scrum being adapted in practice: A systematic review. *Journal of Systems and Software*, *183*, 111110. https://doi.org/10.1016/j.jss.2021.111110

Lycett, M., Rassau, A., & Danson, J. (2004). Programme management: a critical review. *International Journal of Project Management*, *22*(4), 289–299. https://doi.org/10.1016/J.IJPROMAN.2003.06.001

Narbaev, T., & De Marco, A. (2014). Combination of Growth Model and Earned Schedule to Forecast Project Cost at Completion. *Journal of Construction Engineering and Management*, *140*(1), 04013038. https://doi.org/10.1061/(asce)co.1943-7862.0000783

Paasivaara, M., Durasiewicz, S., & Lassenius, C. (2008). Using scrum in a globally distributed project: a case study. *Software Process: Improvement and Practice*, *13*(6), 527–544. https://doi.org/10.1002/spip.402

PMI. (2017). *The Standard for Program Management* (4th ed.).

Pries-Heje, L., & Pries-Heje, J. (2011). Why Scrum works: A case study from an agile distributed project in Denmark and India. *Proceedings - 2011 Agile Conference, Agile 2011*, 20–28. https://doi.org/10.1109/AGILE.2011.34

Putnam, L. H. (1978). A General Empirical Solution to the Macro Software Sizing and Estimating Problem. *IEEE Transactions on Software Engineering*, *SE-4*(4), 345–361. https://doi.org/10.1109/TSE.1978.231521

Schwaber, K. (2004). *Agile Project Management with Scrum (Developer Best Practices)*. Microsoft Press.

Schwaber, K. (2023). *About Scrum.org*. https://www.scrum.org/about

Sutherland, J. (2005). Future of scrum: parallel pipelining of sprints in complex projects. *Agile Development Conference (ADC'05)*, *2005*, 90–99. https://doi.org/10.1109/ADC.2005.28

Sutherland, J., & Schwaber, K. (2011). *The Scrum Papers: Nut, Bolts, and Origins of an Agile Framework*.

Warburton, R. D. H. (1983). Managing and Predicting the Costs of Real-Time Software. *IEEE Transactions on Software Engineering*, *SE-9*(5), 562–569. https://doi.org/10.1109/TSE.1983.235115

Wautelet, Y., Heng, S., Kolp, M., & Mirbel, I. (2014). *Unifying and Extending User Story Models* (pp. 211–225). https://doi.org/10.1007/978-3-319-07881-6_15

Zahraoui, H., & Janati Idrissi, M. A. (2015, December 15). Adjusting story points calculation in scrum effort & time estimation. *2015 10th International Conference on Intelligent Systems: Theories and Applications, SITA 2015*. https://doi.org/10.1109/SITA.2015.7358400