Towards training network resilience to maintain disaster recovery expertise

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ABSTRACT

Effective disaster recovery depends on highly-skilled practitioners. Like any sector, however, the education and training systems that build these skills can experience crises that disrupt their ability to function effectively. These can be one-off events (e.g. a major flood) or extend over long periods (e.g. a pandemic or a vocational crisis). Based on the observation that there is a shortage of trainers and teachers in the education sector, as shown by indicator D7 (OECD, 2023), in this article we study the ongoing ability of a French vocational training organization to transmit skills that are useful to society in the event of a natural disaster, and in particular those that will shorten the recovery time of buildings and infrastructures. We propose a model that simulates the flow of people through the educational system and the institution's ability to generate enough trainers to maintain a chain of know-how transmission. In the simulation of this work in progress, we have parameterized the actual success rates, which we vary in order to define a minimum success rate limit to ensure the renewal of human capital. Based on the proposed model, further testing and analysis will be used to characterize a range of resilient flow behaviors and to provide recommendations for maintaining the condition of the human know-how transmission chain.

Keywords

Resilience, Education System, Evaluation, Key Performance Indicator, Decision Support, Steering

INTRODUCTION

The impacts of climate change on modern societies are still in their early stages. An acceleration in the frequency and magnitude of natural disasters will increasingly lead to damage to people and property (Intergovernmental Panel On Climate Change, 2023). Beyond the public policies implemented to address these crises, it is crucial to recognize the need for skilled workers to help restore, as quickly as possible, the infrastructure, buildings, and industrial facilities essential for the proper functioning of human societies (Bruneau & Reinhorn, 2006). The capabilities required of these workers, in terms of know-how, emotional intelligence, and an understanding of the most effective actions available, take many years to develop and require significant ongoing investment in order to avoid obsolescence (Sandborn & Prabhakar, 2015).

Many of the decision-making skills needed by such expert tradespeople are also needed for effective decision making in other crisis management contexts. For example, it is important to have the capacity to understand complex situations, to withstand stress and pressure, and to make quick decisions, as well as to coordinate and communicate, to demonstrate adaptability, ethics, and responsibility, and to synthesize feedback. These skills therefore represent a critical resource that needs to be developed and maintained in order to avoid a shortage of expertise that could have devastating repercussions in a crisis.

In France, the *Association Ouvrière des Compagnons du Devoir et du Tour de France* (AOCDTF) has been helping to train high-level experts in over thirty trades, mainly in construction and industrial technology, for several centuries. This type of manual know-how enables emergency repairs to be carried out and essential infrastructure to be maintained, such as public buildings, power plants and housing. In so doing, it contributes to the resilience of society.

Here we consider resilience as *"the ability to prepare and plan for, absorb, recover from or adapt more successfully to actual or potential adverse events"* (National Research Council, 2012). The expertise provided by crisis response and recovery organizations is critical for helping society to be resilient, but these organizations may also face disruptions to their own ability to properly train new workers. To play their part in community resilience (Valinejad et al., 2022), therefore, organizations like the AOCDTF (or the *"Compagnons"*) must also have resilient education and training systems, in order to ensure that each organization maintains its own human chain of know-how. This resilience means taking into account the flow of people through the system, and in particular ensuring that the system generates sufficient numbers of graduates and has the capacity to continue doing so. In the case of the *"Compagnons"* organization, this means ensuring that enough young professionals become trainers, so as to maintain the training capacity for the incoming apprentices. When this isn't the case, it creates problems for the organization's economic model, which is then forced to call on former members of the system or external professionals whose remuneration is higher. Furthermore, the pedagogical model of the *"Compagnons"* is based on community life and on there being only a small age gap between learner and supervisor. A disruption in the training system thus also puts pressure on young people who have not yet completed their apprenticeship to take on the job prematurely to fill the gap, which is an undesirable outcome.

With this in mind, this article seeks to contribute to improving the resilience of human capital in training organizations, focusing particularly on the issue of the shortage of trainers for the highly skilled workers needed for disaster recovery efforts. We propose to model the flow of learners and its consequences on the flow of teachers or trainers, in order to better understand the resilience of these educational organizations to internal disruptions, and thus to support decision-makers in their efforts to respond to and recover from such disruptions more effectively. We first introduce a generalized model and provide its mathematical formulation. We then discuss the specific context of the *"Compagnons"* organization in more detail, and apply the model in that specific context, to illustrate its use.

BACKGROUND

Educational systems are intricate organizations, challenging to comprehend to the extent that advanced tools are necessary for modeling them to anticipate their behaviors (Jacobson et al., 2019). Furthermore, such systems are challenging to transform (Burner, 2018), and they often operate in a volatile, uncertain, complex, and ambiguous (VUCA) environment (Waller et al., 2019). This environment exposes such systems to various risks that they must be capable of assessing in order to devise strategies to ensure their proper functioning (Dehdashti et al., 2020). In the face of such complexity, asking questions about resilience such as Meerow et al. (2016)'s five W's (Who? What? When? Where? Why?) is important for allowing educational systems and organizations to gain a broader understanding of the specific context within which they seek to achieve such resilience.

With this in mind, Table 1 enumerates the risks impacting educational systems, classifying them according to the transdisciplinary perspective required for the integration of sustainability and resilience into risk (Nielsen & Faber, 2021). It is self-evident that these risks are not exhaustive, and each educational organization must undertake a comprehensive survey tailored to its environment.

Our focus here is on the trend towards a shortage of teachers within such systems, which is a challenging phenomenon because it unfolds over an extended period of time. It offers an example of a so-called "slow-motion disaster" (or "slow-onset disaster") where the impacts (in this case, a corresponding shortage of highly skilled workers) are not immediately felt. Pierrehumbert (2006), in discussing climate change and carbon dioxide emissions, defines slow-motion disasters as events where the consequences manifest over a century or more. Draus (2009), in the study of Detroit's population and drawing on numerous other works, refers to slow-motion disasters by focusing on the consequences of multiple vulnerabilities that can accumulate and whose effects become visible over the long term. He introduces a sociological component, represented by a cascade of cause-and-effect relationships. Additionally, he identifies slow-motion disasters at the structural, process, or situational state levels.

Table 1. Risks in Educational Organizations

Risk Family	Risk	Capacity from / to
Human Assets	Lack of trainers	Managing human resources
	Excessive attrition rate	Supporting learners
	Demographics	Adapting the organization
Production	Teaching obsolescence	Update skills
	Reputation	communicate
	Cheating	Fostering integrity
	Operational under-performance	Leading and empowering staff
Health	Psycho-social	Taking care of people
	Contagiousness	Organizing health constraints
Earth system, Environment, Food, Water, Natural resources	Ethics	Training stakeholders
	Environmental	Minimizing the organization's footprint
	Shortages	Securing supply
Economy	Budget limits	Manage fluctuations
	Corruption	Control integrity
Systems engineering, Infrastructures, Free market systems, Governance	Universal access uncertainty	Plan
	Organizational under-performance	Continuous improvement
	Technological disruption	Adapt strategy
	Administration	Organize and plan for the future
	Competition and globalization	Satisfy stakeholders
	Legal	Track activities
	Regulatory	Ensure compliance
	Crisis management	Prepare for action

The evaluation of educational systems is most often used for assessment rather than for guidance (Michel, 2000), and there can be challenges with accepting evaluation by those involved in vocational education (Jorro, 2007). Our ambition is to provide indicators that can contribute to both measuring and improving the resilience of human trainer resources in this context. We thus need to know inputs, outputs, objectives, and instructions, as well as human, technical, and financial resources, in order to appropriately characterize how such an organization functions. To evaluate the behavior of these processes, we then also need to have key performance indicators (KPIs) at our disposal that will enable us to measure effectiveness (which is the relationship between objectives and result), efficiency (which is the relationship between means and results), and relevance (which is the relationship between means and objectives) (Nadoveza Jelic et al., 2018; Saikia & Bezborah, 2014).

MODEL

To support evaluating the resilience of educational systems in the context of slow-motion disasters, we propose a discrete, generalizable mathematical model that represents the flow of individuals—learners, graduates, and trainers—through time.

By creating this model, we aim to reach two goals: to have a better overall understanding of the dynamics of the system and to be able to answer questions such as the following, in order to guide resilience-focused decision making:

- What is the sustainable growth level of the system?
- What happens if the rate at which learners become trainers varies upward or downward?
- What occurs if the inflow rate slows down (due to demographic changes, different choices of orientation by entrants, etc.)?
- What happens in the event of a crisis (i.e., a sudden decrease in learners or trainers)?

Because of the length restrictions of a work-in-progress paper such as this, our discussion below focuses on only one such question, illustrating the potential of the new mathematical model by analyzing the effect of changes in the student attrition rate.

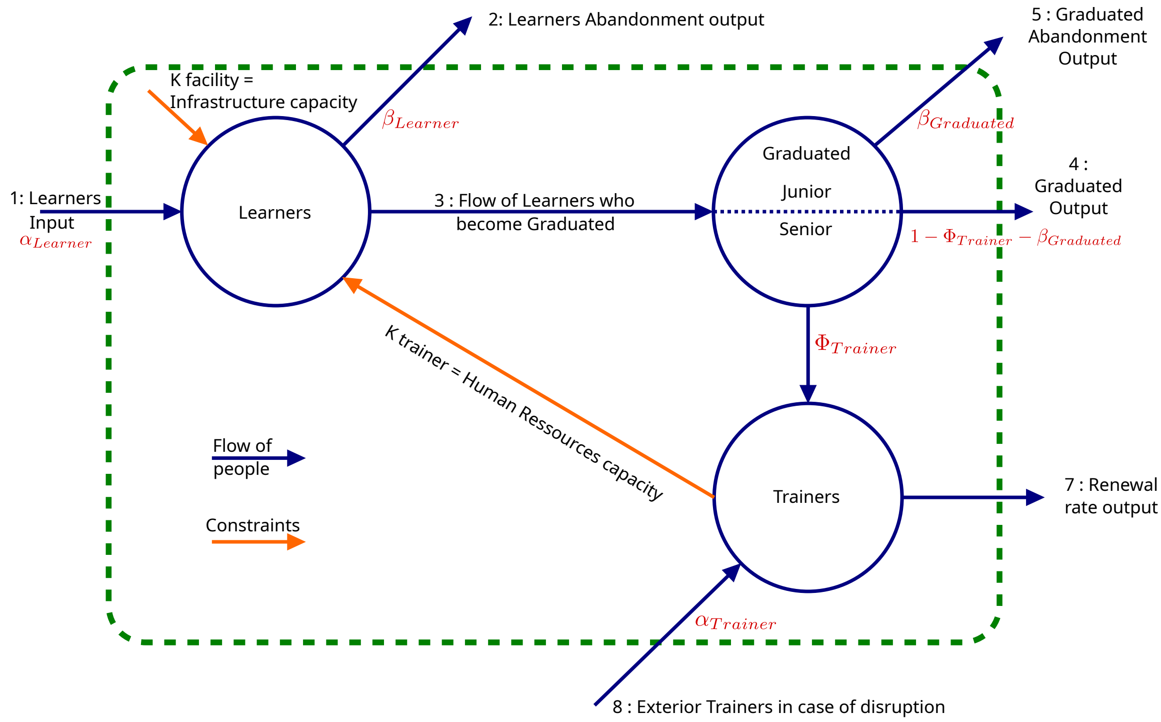

Figure 1. Trainer flow model

In order to enable an education system's managers to project their available human resources (i.e., the personnel who serve as trainers), we propose the model shown in Figure 1. In this model there are 3 pools of resources :

- The Learners : The behavior of the Learners in the system is defined by equation (1). The training will last a duration of $\tau_{Learner}$ years. Each year the pool of learners will suffer losses $\beta^t_{Learner}$ due to drop-out, reorientation, or breach of contract between the learner and the host company (flow 2). Those who will succeed through all the training will be the input of the Graduated pool.
- The Graduated : The behavior of the Graduated in the system is defined by equation (2) and equation (3). A Graduated is first a Junior for one year before becoming a Senior. These graduates may subsequently use their expertise to support the training efforts for an additional period of time, with this group also suffering $\beta_{Graduated}$ losses due to abandonment and other reasons (flow 5). After a certain time, τ_{Senior}, a compliant flow out of the system takes place, for reasons of career development, updating of knowledge, or other reasons (flow 4). A proportion $\Phi^t_{Trainer}$ of Senior graduates will then change state to become the input flow of the Trainers pool.
- The Trainers : The behavior of the Trainers in the system is defined by equation (4). Trainers will stay for time $\tau_{Trainer}$ before leaving the system (flow 7). In the event of a shortage of trainers, it is possible to call on external sources of trainers: $\alpha^t_{Trainer}$ (flow 8).

We also have added several infrastructure constraints: $K_{Facility}$ is the capacity of the training centers, representing the upper limit of learner intake, and $K_{Trainers}$ is the ideal number of trainers needed for the system to perform as expected. Based on this description of the training system, we introduce the associated mathematical flow model. The relevant parameters on which the flow model is based are as follows :

- τ_{Learner} : the duration of the training.
- τ_{Senior} : the minimum time before leaving the system as a Graduate.
- $\tau_{Graduated}$: the minimum time before becoming a Trainer.
- $\tau_{Trainer}$: the minimum time before leaving the training system.
- $\Phi^t_{Trainer}$: the Trainer transformation rate: the portion of the Graduated that will become Trainers
- $\beta^t_{Learner}$: the Learner abandonment rate
- $\beta_{Graduated}$: the Graduated abandonment rate, before becoming either a Senior or a Trainer

- $\alpha_{Learners}$: the input of Learners each year.
- $\alpha^t_{Trainer}$: the input of external Trainers each year.

$$\begin{aligned} Learner^t_1 &= \alpha^t_{Learner} \\ Learner^t_i &= Learner^t_{i-1}\left(1-\beta^t_{Learner}\right) && \forall i \in [2, \tau_{Learner}] \end{aligned} \tag{1}$$

$$\begin{aligned} Graduated^t_1 &= Learner^t_{\tau_{Learner}}\left(1-\beta^t_{Learner}\right) \\ Graduated^t_i &= Graduated^t_{i-1}\left(1-\beta_{Graduated}\right) && \forall i \in [2, \tau_{Graduated}] \end{aligned} \tag{2}$$

$$\begin{aligned} Senior^t_1 &= Graduated_{\tau_{Graduated}}\left(1-\beta_{Graduated}-\Phi^t_{Trainer}\right) \\ Senior^t_i &= Senior^t_{i-1}\left(1-\beta_{Graduated}\right) && \forall i \in [2, \tau_{Senior}] \end{aligned} \tag{3}$$

$$\begin{aligned} Trainer^t_1 &= Graduated_{\tau_{Graduated}}\Phi^t_{Trainer} + \alpha_{Trainer} \\ Trainer^t_i &= Trainer^t_{i-1} && \forall i \in [2, \tau_{Trainer}] \end{aligned} \tag{4}$$

The parameters $\Phi^t_{Trainer}, \beta^t_{Learner}$ and $\alpha^t_{Trainer}$ are time dependent and will vary depending on the system regime. Three types of regime are defined in equation (5) and differentiated by the learner supervision rate as follows:

- Regime 1, which incorporates over-capacity utilization of the organization (one trainer for more than X2 learners). This situation will lead to a deterioration in service in terms of quality of welcome, supervision, and ultimately success.
- Regime 0, which represents operations as designed, with one trainer responsible for training X1 to X2 learners.
- Regime -1, which represents under-utilization of capacity, with fewer than X1 learners for one trainer.

Regimes 1 and -1 are undesirable, as the former degrades service quality while the latter is not financially sustainable.

$$Regime = \begin{cases} 1 & \text{if } Learners \geqslant K_{Trainers} \text{ or } Learners \geqslant K_{Facility} \\ -1 & \text{if } Learners \leqslant X1 \\ 0 & \text{if } X1 \leqslant Learners \leqslant X2 \end{cases} \tag{5}$$

USE CASE

We now provide a specific example of applying the model above. The chosen example concerns the influence of the educational system's efficiency on maximizing the flow of learners to complete a full course in a French vocational training establishment, and its consequences for trainers' critical resources.

The *"Compagnons du Devoir"* vocational training system is based on the principle of traveling to learn a trade by gaining experience in different companies. After initial training, young company employees and work-study students travel from one training center to another, in France and abroad, to acquire the knowledge and skills specific to the trade they are learning. The training, accommodation, and catering facilities have been managed by associations of former beneficiaries of the scheme since the Middle Ages, forming a collaborative network for multiple trades where knowledge, know-how and interpersonal skills are exchanged.

As a highly skilled workforce, spread across the network of companies for which they work, the people trained by the *"compagnonnage"* system contribute to the restoration of infrastructures damaged by natural disasters. This takes the form of underpinning and reinforcement work, waterproofing when roofs are damaged, or repair work on industrial sites, depending on the type of damage. Each of these capabilities, taken together, will enable a building, an infrastructure component, or a piece of equipment to return to a functional state, thus ensuring the resilience of society as a whole.

"Compagnonnage" needs to design and ensure its resilience through the transmission of specific skills that can only be learned through experience. Over the last ten years, the number of apprentices joining the AOCDTF has doubled from $1,500$ to $3,000$. The training cycle lasts between 5 and 7 years, and the vast majority of trainers come from the end of the training course. Once they have become *"Compagnons"*, and have benefited from free,

Table 2. Assumptions on simulation initialization parameters

Parameters types	Definition	Values
$\tau_{Learners}$	the duration of the training	6 years
τ_{Senior}	the minimum time before leaving the system as a Graduate	3 years
$\tau_{Graduated}$	the minimum time before becoming a Trainer	1 year
$\tau_{Trainer}$	the minimum time before leaving the teaching system	2 years
$\Phi^t_{Trainer}$	the trainer transformation rate: graduated that will become trainer	50%
$\beta^t_{Learner}$	the learner abandonment rate (attrition rate)	35%
$\beta_{Graduated}$	the graduated abandonment rate, before becoming Senior or Trainer	10%
$\alpha^t_{Learner}$	the input of learners each year	417 per year
$\alpha^t_{Trainer}$	the input of external trainer each year	result of balance

high-level training, highly-skilled young workers commit to staying with the organization for 3 years, passing on the knowledge they have acquired to younger workers. This is the "Duty" that the *"Compagnons"* will carry out by becoming a trainer, or by continuing to travel and supervise the system of evening classes enabling workers to be promoted. 90% of young journeymen respect this commitment. They are the critical resource for the smooth running of the system. This 3-year transition time between graduation and leaving the system is taken into account and could be compared in the academic world to the situation of a doctoral student who for 3 years after obtaining a degree will continue to progress in his or her field of expertise until leaving the training process.

By simulating the training process for the *"Compagnons"* organization via the mathematical model derived above, we aim to answer the question: *"What happens when the attrition rate changes"* or *"What is the impact of improving the success rate?"* Studying the behavior of these variations will enable us to estimate the limits and regime changes facing the organization. We are basing our model on real data from *"Compagnons"* carpenters, in order to verify its conformity with reality.

We therefore experiment with the mathematical model, as implemented in Python, varying the attrition rate ($\beta^t_{Learner}$) to characterize the associated changes in system behavior. The initial conditions are given in Table 2.

RESULTS AND DISCUSSION

As shown in Table 3, we can see the variation in the annual attrition rate (AR), which accumulated over 6 years gives us the success rate (SR). We can see from the simulation results that, with an annual attrition rate of 35% of the workforce, if we start with 417 learners, after 6 years we still have 31 carpenters who have become *"Compagnons"*. Considering that 50% have the capacity to be trainers, this means a potential number of between 15 and 16, which is not enough to cover the annual requirement of 17 carpenter trainers. When we increase the attrition rate to 36%, we find that the number of *"Compagnons"* carpenters falls by a further 3 units, worsening the trainer deficit to -3 positions and -4.5 positions for 37% attrition. Similarly, by varying the attrition rate downwards, the simulation results show that the trainer balance becomes positive again at 33%, even releasing a potential of 2 additional trainers for each percentage point gained.

As listed in Table 1, in our future work we will be testing a range of risk factors specific to maintaining human capital, i.e. the lack of trainers, the attrition rate, and demographics, by testing extreme scenarios. By simulating the flow of people, we can also test the economic impact on the organization, as well as the budgetary limits of these fluctuations. As far as systems engineering is concerned, this flow simulation system contributes to planning, continuous improvement, updating strategy, and projecting the organization's administration into the future. All of these risk factors, which represent a range of real-world issues, give us confidence that organizations addressing these risks will become more resilient.

By testing these risk factors, we will accumulate information that will enable us to better understand the behavior of knowledge and know-how transmission systems. This will help us to more fully answer a variety of research questions, such as those posed at the beginning of the Model section, and thus help us to more effectively characterize the sustainability, limits, speeds and crisis sensitivity of human skill and knowledge chains.

Table 3. Carpenters simulation results

AR: Attrition Rate; SR: Success Rate; TR: Trainer Requirements; TB: Trainers Balance

AR/year(%)	SR after 6 years(%)	*Compagnons*	Variation	Annual TR	TB
37	6.0	25	−6	17	−4.5
36	6.7	28	−3	17	−3.0
35	7.4	31	0	17	−1.5
34	7.9	33	2	17	−0.5
33	8.6	36	5	17	1.0
32	9.6	40	9	17	3.0
31	10.6	44	13	17	5.0
30	11.5	48	17	17	7.0
29	12.5	52	21	17	9.0

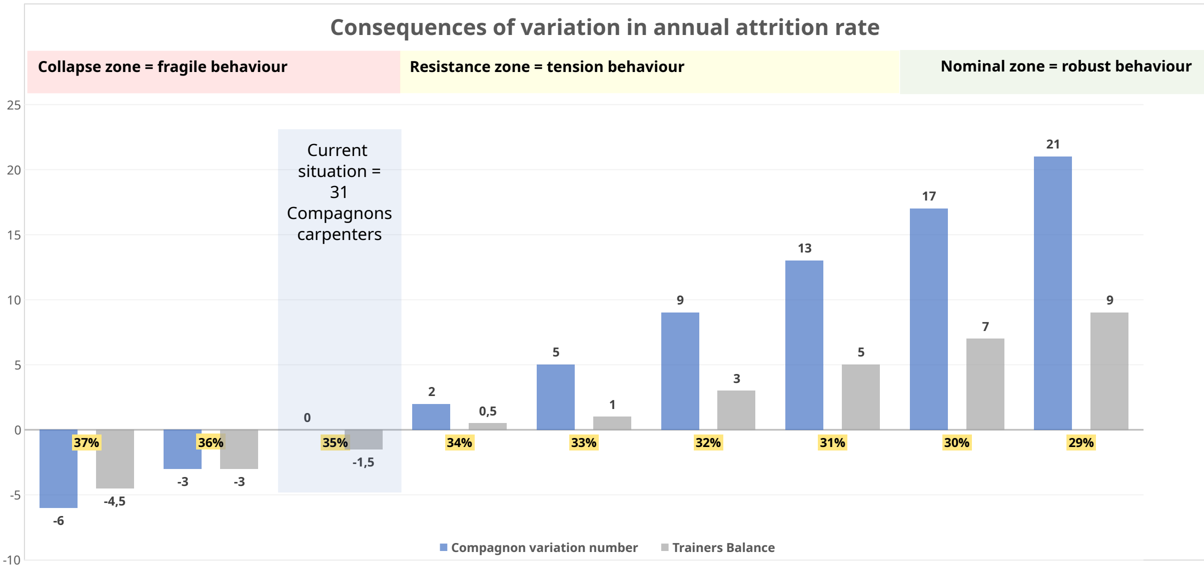

Figure 2. Attrition rate variation

ANALYSIS

Figure 2, which shows the variation in the percentage of attrition, enables us to analyze the preliminary results. The x-axis shows the variation in the attrition rate between 37% and 29% of the workforce, while the y-axis shows the workforce balance. The current benchmark of 35% is unsustainable, as it generates a chronic shortage of trainers. We have decided to position the simulations showing a trainer deficit in the collapse zone, which reveals the system's fragile behavior. We have arbitrarily chosen to place the scenarios between 34% and 31% in the resistance zone, which reveals that the system is under stress. We consider that in the case of *"Compagnons"*, from 30% attrition per year, the system remains in the nominal zone, suggesting robustness with constant behavior.

MODEL LIMITATIONS

This is a first version of our vision of the behavior of a learner flow in a know-how chain perspective, and like any model under construction, it does not claim to predict an indisputable result in an exact and precise manner. However, it is already useful for understanding the principles of circulation of flows of people transmitting knowledge, and can be used to estimate whether the system is in tension or not.

Attrition rates are parameterized linearly, whereas they tend to follow an irregular slope, with a sudden loss at the end of the 2^{nd} year approaching 75%. This will be taken into account in the next iteration of model improvement, but in our case has no impact on the final number of trainers. This will help us to assessing the potential stock of learners, which is of interest for estimating the sizing of future infrastructures and the demand for trainers.

At this stage, we have not yet modelled regime changes. The various experiments we are going to simulate should enable us to define a high and low threshold for assessing the resilience of the transmission chain as practiced by the

"Compagnons". Empirically, it is generally accepted that an apprentice section is viable from 12 learners upwards, and that it becomes difficult to supervise more than 20 learners without degrading the quality of supervision, notably for safety reasons. We will integrate the consequences of these regime variations by giving ourselves the possibility of increasing the attrition rate as soon as the regime moves into overcapacity, and to parameterize a section collapse rule in the case of understaffing, starting from limits to be defined during our future simulations.

The model was initially implemented in Python, and a range of different outcomes were generated deterministically by varying the attrition rate and the number of incoming learners. Future extensions include further incorporating stochastic behavior in order to better characterize the range of possible outcomes.

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

As mentioned above, the *"Compagnons organization"* is currently experiencing a growth crisis of varying severity, depending on the trade. For Carpenters, the average annual need for trainers is 17. If we consider that one out of every two *"Compagnons"* has the capacity to become a trainer, we can immediately see a chronic deficit of 1.5 trainer positions, which accumulates over the 2-year cycle and is confirmed by the interviews conducted with *"Compagnons"*. By varying the loss rate downwards in 1% steps, we can see the effects of making the balance positive from 33% loss, by releasing a sufficient number of journeymen with the capacity to be trainers, and thus covering the need.

These results show how the organization is behaving, and make it more straightforward for managers to become aware of the situation by providing them with the tools they need. Simulating learner flow makes it easier to understand the issues involved in maintaining the ability to transmit know-how or knowledge. This insight highlights the importance of questioning the *"Compagnons"* training system, so that it pays greater attention to the success rate of learners, which is one of the keys to renewing this human chain of know-how. It also indicates that this type of model could be helpful in other long-term training contexts where shortages are already identified, such as in healthcare services or civil security.

With regard to the model, we will continue our efforts to improve it, taking into account the fact that the attrition rate is not linear, so as to be able to forecast the number of learners, grads, and trainers per year with greater reliability. We will also implement the possibility of simulating a regime change to vary success rates by an additional factor. This will bring us closer to real-life behavior, where we can observe a deterioration in success rates when staffing levels are insufficient, or when a training course eventually disappears due to low enrollment. Ultimately, many factors need to be identified and combined in order to fully answer our research questions.

It is, of course, also important to recognize that many different types of crises can disrupt education systems over extended periods of time, such as armed conflicts resulting in conscription of young people (collapse of incoming numbers), demographic crises (fewer births and consequent drop in incoming numbers), financial crises (drying up of apprenticeship funding), vocational crises (poor image of manual trades), reputational crises (trades perceived as degrading for society following a news item resulting in a bad reputation), or public health crises (confinement preventing professional practice). Furthermore, although we have focused here on such slow-motion disasters, sudden-onset disasters such as floods, wildfires, major storms, or terrorist attacks can also impact the proper functioning of an education system in a number of different ways. The impacts of such events could also be incorporated into the simulation model through their effects on training times and abandonment rates; however, to fully explore this more traditional disaster management context it will help to develop a more detailed flow model that incorporates more of the logistics of the training process.

The differentiation of the organization's behavior into three types - fragile, resistant or robust - still needs to be qualified and tested in our next iterations of the model. Once we have gathered the available data to align as closely as possible with reality, we will be able to test the behavior of different scenarios. We will implement an experimental design by varying key parameters, thereby gaining the ability to make recommendations.

In order to evaluate the resilience of the knowledge chain, we will test our model to define its resistance thresholds. A design of experiment will therefore be conducted to observe the system's absorption capacity according to scenarios of input flow and attrition rate variability. We will also observe its recovery time under different hypotheses. Finally, we will assess the potential for adaptation in order to prescribe recommendations for improving the overall resilience of the chain and avoiding disruptions that have consequences in terms of loss of know-how and societal capacity to cope with natural disasters.

There are 36 *"Compagnons"* trades, each with a different learner flow behavior and resilience level. Once the model has been tested, we'll be able to diagnose this behavior, make appropriate recommendations, and assist decision-makers by simulating the potential impact of their wishes. Once all 36 scenarios have been aggregated, we will also be able to identify a trend in the resilience behavior of the *"Compagnons"* organization as a whole, first of all to trainer shortages, but ultimately to a wide variety of different types of disruption. This, in turn, will support the organization's ongoing efforts to continue training new members and it will allow them to continue providing the necessary expertise to make our critical infrastructures more resilient.

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