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A simulation based digital twin approach to assessing the organization of response to emergency calls



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In emergency situations, timely contact with emergency medical communication centers (EMCCs) is critical for patient outcomes. Increasing call volumes and economic constraints are challenging many countries, necessitating organizational changes in EMCCs. This study uses a simulation-based digital twin approach, creating a virtual model of EMCC operations to assess the impact of different organizational scenarios on accessibility. Specifically, we explore two decompartmentalized scenarios where traditionally isolated call centers are reorganized to enable more flexible call distribution. The primary measure of accessibility was service quality within 30 s of call reception. Our results show that decompartmentalization improves service quality by 17% to 21%. This study demonstrates that reducing regional isolation in EMCCs can enhance performance and accessibility with a simulation-based digital twin approach providing a clear and objective method to quantify the benefits.”

Territorial organization of the emergency call response is essential. For the most serious patients, immediate contact with an emergency medical communication center (EMCC) is vital. Patient morbidity and mortality are directly linked to the time it takes to answer a call, guide life-saving techniques via the telephone, deploy rescue and emergency care resources, and activate specialized hospital care channels^{1,2}.

In France, the response to emergency calls is compartmentalized: each department (an administrative area of 75,000 to more than two million people) generally has an EMCC that handles emergency calls only within its territory. The current organization directs all emergency calls from an administrative area to the EMCC in that department, even if it is overloaded. The organization of EMCCs in France was established by the 1986 law on pre-hospital emergency medicine. Each EMCC was developed independently without a national master plan and they were constrained by the technical equipment available at the time. The departmental structure was considered a logical geographic unit for organizing emergency services. The consequences of this compartmentalization are mainly highlighted during daily working hours with call peaks, particularly when the number of agents is not sufficient to answer the calls: waiting times before answering can

exceed the maximum limits set (30 s). In addition, influenza, a seasonal epidemic or a health crisis such as COVID-19 in 2020 and 2021 may place varying demands on the emergency system. The central role of EMCCs is managing urgent care requests in order to provide an appropriate response to patient care needs and preserve overall hospital operations³. The COVID crisis also highlighted the current difficulties associated with medical and economic constraints as well as staff shortages within a structure that has seen a constant increase in activity over the last 15 years. Many countries have also been affected by this widespread phenomenon which has had an impact on emergency response, in particular during busy periods⁴. Against this backdrop, prehospital care organizations must be evaluated to identify factors for improvement.

Studies on contact with EMCCs are scarce despite the fact that this stage is the first link in the emergency care chain. The literature focuses mainly on characterization of the situation and the time between when the call is answered and arrival of the emergency ambulance at the scene^{5,6}.

A few studies have shown that it is also important to improve the initial reception stage of incoming calls to ensure that they are answered quickly by an emergency call operator (ECO)^{7,8}. However, these latest studies remain

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Table 1 | Summary of simulation results for Scenario #1: partitioned organization (baseline)

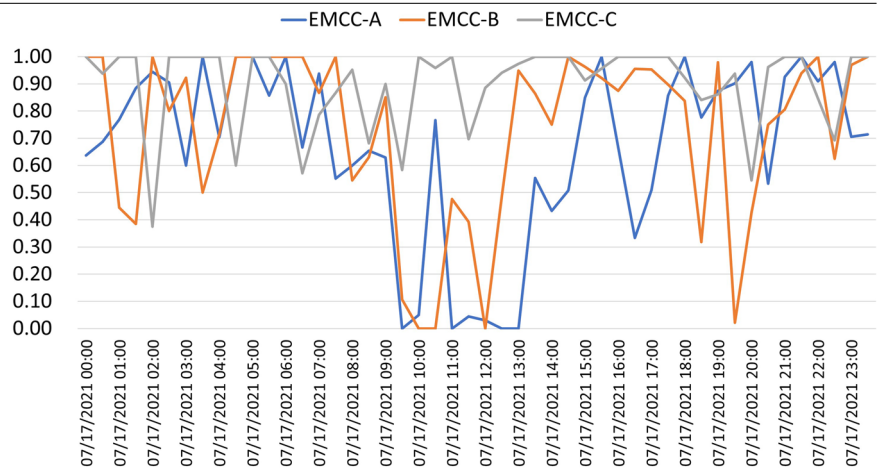
	Incoming Calls from each admin. dept.	Abandon + Lost calls in each queue	Answered calls	AQoS ₃₀ Aveg.	QoS_30i, CoV
EMCC-A	14,662	1511 [1482; 1539]	13,151 [13,123; 13,178]	74% [73.4%; 75.3%]	±39% [37.0%; 40.5%]
EMCC-B	10,671	1033 [1023; 1042]	9638 [9629; 9648]	82% [81.1%; 83.3%]	±28% [25.7%; 29.6%]
EMCC-C	5973	519 [506; 531]	5454 [5442; 5467]	89% [87.9%; 90.2%]	±17% [16.1%; 18.7%]
Overall	31,306	3063	28,243

AQoS₃₀ Aveg.: Average value of Quality of Service at 30 s.

QoS_30i, CoV: Coefficient of Variation of 30-min slot Quality of Service at 30 s for each slot *i* (*i* = 1 to 336).

The values in brackets correspond to the lower and upper limits of the 95% confidence interval, except for the incoming calls because the values are the same on each replication.

Fig. 1 | Overview of the variability of QoS_{30i} on one day (07/17/2021) for scenario #1 (As-Is: Partitioned). It illustrates an example for a single day of the week (17/07/2021) of the variation in quality of service for each slot (QoS_{30i}) over the 336 30-min slots in the week (from ±17% to ±39%). The target value of 99% was not achieved but in some time slots no incoming call was answered in less than 30 s.



largely observational since it is difficult to test new organizations in an interventional design without the risk of destabilizing a system that is working 24/7, is already under stress and is not very resilient.

In the literature, there are two main scientific approaches to this problem: queueing theory and simulation. Several authors have highlighted the limitations of queueing theory⁹.

Fortunately, recent advances in information science have led to the development of methods and tools to simulate complex systems. Multi-agent modeling, for example, is frequently used in epidemiology¹⁰ and many other methods were used in public health during the COVID-19 pandemic¹¹. More recently, the concept of “digital twin” has entered the field of medical research and opened up numerous possibilities to improve care and diagnosis^{12–14}. A digital twin is a digital model that is created to accurately reflect an existing physical object^{15–17}. It is also useful for healthcare facility management and decision-making^{18–22}. The boundary between simulation and digital twin is not always the same, depending on the areas of application and uses. Even if recent standards like ISO/IEC 30173:2023 attempt to give a consensual definition, the abundant literature of recent years shows a very wide dispersion of the interpretation of the term digital twin by the scientific community, manufacturers, and solution providers, that reflect the need for associating a maturity level to each digital twin. The next ISO/IEC 30186 standard (in preparation to be published in 2025) will provide guidance for maturity assessment. On the other hand, it appears to be established that a digital twin is the virtual replica of an existing real system and that there is no digital twin without simulation, whereas the opposite is possible when the real system does not exist. While traditional data-driven modeling focuses on analyzing historical data for insights, digital twins provide a dynamic, real-time representation of the physical system. This enables continuous monitoring if the digital twin is

synchronized in real-time to the real world. The connection and synchronization between the physical system and the digital twin is out of the scope of this study. We can just mention that we connect and feed our digital twins with real world data, but not in real-time. Indeed, in this study, the digital twin made it possible to replay simulations of the existing configuration, and to run simulations of non-existent configurations to assess if they are better or not. This study is therefore being conducted using a simulation-based digital twin approach^{23–27}. The concept of the digital twin is now well accepted in the medical community in a variety of forms ranging from digital twins of organs in the human body, or of its metabolism, to digital twins of healthcare operational processes such as patient pathways¹³.

Our hypothesis was that a simulation-based digital twin approach could help quantify the potential impact of different decompartmentalization scenarios to increase accessibility of call centers to the population. Thus, the aim of our work was to use this new approach to rapidly assess the potential impact of the decompartmentalization of EMCCs on their quality of service without affecting their actual activity.

Results

Scenario #1: partitioned organization

Table 1 shows the simulation results obtained for each of the three EMCCs in the study in the existing configuration. It should be noted that the average value of quality of service (AQoS₃₀) target (99%) was not reached in any EMCC during this week of high activity. Figure 1 shows an example of only one day of the week (07/17/2021). There was a very high variability of the quality of service for each slot (QoS_{30i}) over the 336 30-min slots of the week (±17% to ±39%). Not only was the target value of 99% not met, but in some time slots, no incoming call was picked up in under 30 s.

Table 2 | Summary of simulation results for Scenario #2: interconnected organization

	Incoming calls from each admin. dept.	Abandon + Lost calls in each queue	Overall answered calls	Including outside calls	AQoS ₃₀ Avge.	QoS _{30i} CoV	AQoS ₃₀ Avge.Diff./Baseline	AQoS ₃₀ CoV Diff./Baseline
EMCC-A	14,662	1291 [1271; 1311]	11,987 [11,910; 12,063]	1349 [1263; 1436]	98% [97.9%; 98.5%]	±6% [4.5%; 6.7%]	+32%	-85%
EMCC-B	10,671	921 [910; 933]	9694 [9590; 9799]	2031 [1947; 2115]	99% [98.6%; 99.1%]	±4% [3.1%; 4.8%]	+21%	-86%
EMCC-C	5973	476 [464; 488]	6939 [6866; 7006]	2,877 [2783; 2970]	99% [99.4%; 99.8%]	±2% [0.9%; 2.4%]	+11%	-88%
							average	average
Overall	31,306	2688	28,620	6257			+21%	-86%

AQoS₃₀ Avge.: Average value of Quality of Service at 30 s.

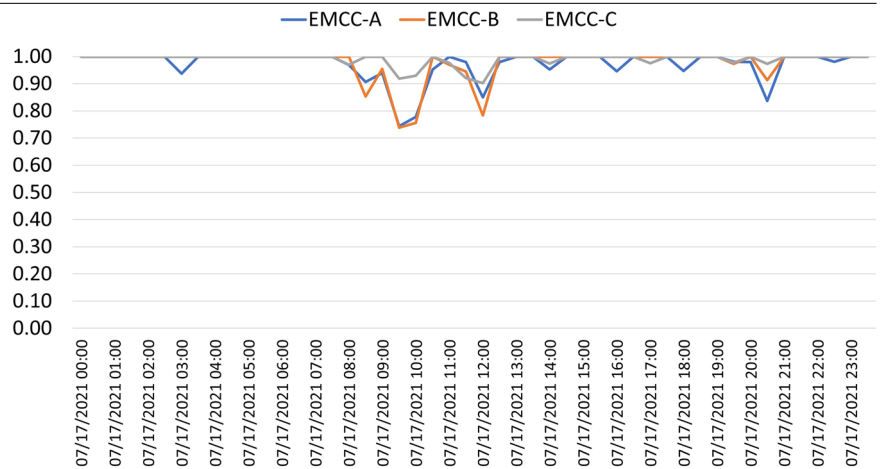
QoS_{30i} CoV: Coefficient of Variation of 30-min slot Quality of Service at 30 s for each slot *i* (*i* = 1 to 336).

AQoS₃₀ Avge. Diff./Baseline and AQoS₃₀ CoV Diff./Baseline: Relative deviation from existing configuration: 100 x (interconnected - existing) / existing.

Diff./Baseline: relative difference with the results from the existing organization (partitioned).

The values in brackets correspond to the lower and upper limits of the 95% confidence interval, except for the incoming calls because the values are the same on each replication.

Fig. 2 | Overview of the variability of QoS_{30i} on one day (07/17/2021) for scenario #2 (Inter-connected). It highlights a remarkable result: the variability of QoS_{30i} is considerably reduced compared with the reference scenario. Even if the target of 99% QoS₃₀ is not achieved in EMCC-A, the values are significantly improved (+11% to +32%) compared with scenario 1.



Scenario #2: interconnected organization

Table 2 collates the results obtained for an interconnection of the three EMCCs. As can be seen, there is a marked improvement in the AQoS₃₀ with this organization. It reaches the target of 99% in two EMCCs and 98% in EMCC-A. The AQoS₃₀ gain compared with scenario #1 is 11% for EMCC-C and 32% for EMCC-A. Another remarkable result is the significantly reduced variability of QoS_{30i}, as Fig. 2 shows. Indeed, the coefficient of variation (CoV) did not exceed ± 6% around the average value AQoS₃₀ (EMCC-A) with a reduction of 85% compared with the baseline. Even if the 99% target of AQoS₃₀ is not reached in EMCC-A, values are significantly improved (+11% to +32%) compared with scenario #1. For the same number of incoming calls as in Scenario #1, the number of calls answered increased slightly (+1.3%).

Scenario #3: organization in virtualized mode

Table 3 summarizes the simulation results in virtualized mode. Although lower than for the previous scenario (interconnected), there is a clear improvement in AQoS₃₀ compared with the existing situation: +6% for EMCC-C and up to 30% for EMCC-A. This organization helped balance service quality in the three EMCCs. With this virtualized organization, the variability of QoS_{30i} is improved comparing with the existing one, but is less significantly than the interconnected one (Fig. 3). Indeed, the CoV did not exceed ±30% around the average value AQoS₃₀ (EMCC-A) with a reduction of 67% compared with the baseline.

Tables 2 and 3 also illustrate the number of calls coming from “outside” areas for Scenarios #2 (interconnected) and #3 (virtualized).

Discussion

The results obtained from this study highlight the positive impact that decompartmentalization can have on EMCC quality of service: an average 17-point improvement (+22%) for interconnection and 13 points for virtualization (+17%) with homogenization of performance between the three centers. As a result, the occupancy rate of ECOs at the three EMCCs also needs to be very balanced which can be an important managerial argument to convince teams of the benefits of such an organizational change. Even if the results are not as good in absolute terms as with the interconnected mode, this organization should be taken into account for real implementation in EMCCs. The difference of QoS between interconnection and virtualization is due to the structure of the queuing network. In the interconnected mode, there are three waiting queues working in parallel, each of them receiving its incoming calls from its administrative region, while there is only one queue in the virtualized mode receiving all the incoming calls from all of the regions.

The impact of the Covid-19 pandemic on the increase in EMCC activity must be considered. New remote simulations should be performed.

The use of an EMCC digital twin therefore enabled us to use real production data to identify the organizational strategies with the greatest

Table 3 | Summary of simulation results for Scenario #2: virtualized organization

	Incoming calls in the unique queue	Abandon + Lost calls from the unique queue	Overall answered calls	Including outside calls	AQoS ₃₀ Avge.	QoS _{30i} CoV	AQoS ₃₀ Avge.Diff./Baseline	AQoS ₃₀ CoV Diff./Baseline
EMCC-A	31,306	2728 [2701; 2754]	10,497 [10,431; 10,562]	5566 [5495; 5637]	95% [94.7%; 95.6%]	±13% [11.6%; 15.2%]	+30%	-67%
EMCC-B			9818 [9765; 9871]	6473 [6424; 6523]	95% [94.7%; 95.6%]	±13% [11.0%; 14.3%]	+16%	-54%
EMCC-C			8263 [8199; 8327]	6660 [6571; 6749]	95% [94.9%; 96.0%]	±13% [11.2%; 14.9%]	+6%	-24%
							average	average
Overall	31,306	2728	28,578	18,699			+17%	-48%

AQoS₃₀ Avge.: Average value of Quality of Service at 30 s.

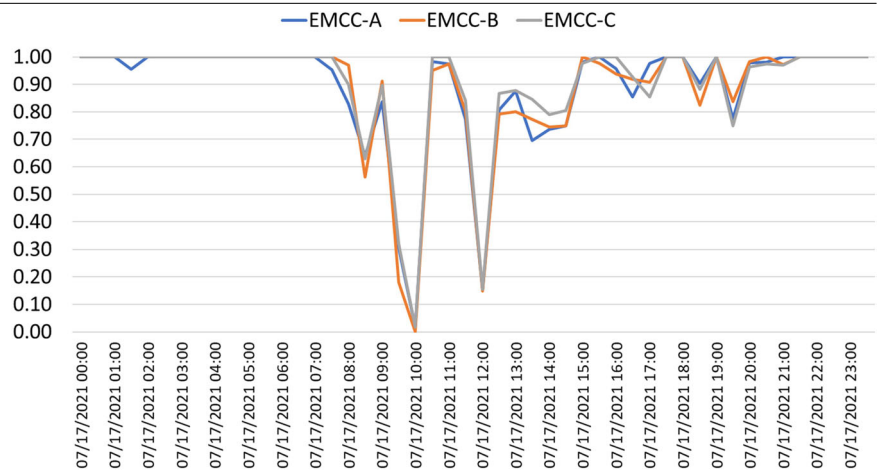
QoS_{30i} CoV: Coefficient of Variation of 30-min slot Quality of Service at 30 s for each slot *i* (*i* = 1 to 336).

AQoS The values in brackets correspond to the lower and upper limits of the 95% confidence interval, except for the incoming calls because the values are the same on each replication.

AQoS₃₀ Avge. Diff./Baseline and AQoS₃₀ CoV Diff./Baseline: Relative deviation from existing configuration: 100 x (virtualized - existing)/existing.

The values in brackets correspond to the lower and upper limits of the 95% confidence interval, except for the incoming calls because the values are the same on each replication.

Fig. 3 | Overview of the variability of QoS_{30i} on one day (07/17/2021) for scenario #3 (Virtualized). It presents the effect of the virtualized scenario. With this organization, the variability of QoS_{30i} is improved compared with the existing organization, but is less than with the interconnected organization.



potential for improving performance without altering current center operations, thereby maintaining service quality and user safety. Once the model was built, the use of simulation tools also offered the significant advantage of testing scenarios much more quickly and flexibly than real-life experimentation: the parameters linked to organization or patient flow can easily be modified and a week’s activity can be simulated in just a few minutes on a sufficiently powerful computer. This flexibility means that our approach can be transposed to other EMCCs regardless of the country or healthcare system.

In healthcare, the advantages of simulation have long been recognized and numerous methods have been implemented to solve a wide range of problems: system dynamics simulation, agent-based simulation or discrete-event simulation^{28–30}. In the specific field of emergency medical intervention, the literature on digital twins remains scarce and our study provides a novel contribution. Madhiraji et al., for example, presented a framework for modeling the entire emergency care chain: from an emergency call to treatment³¹. There is even less simulation work limited to the scope of emergency call centers. Van Buuren et al. proposed a detailed model of an EMCC, including two sequential queues to simulate not only the ECO process, but also a dispatcher process for dispatching an ambulance and finding a receiving hospital^{32,33}.

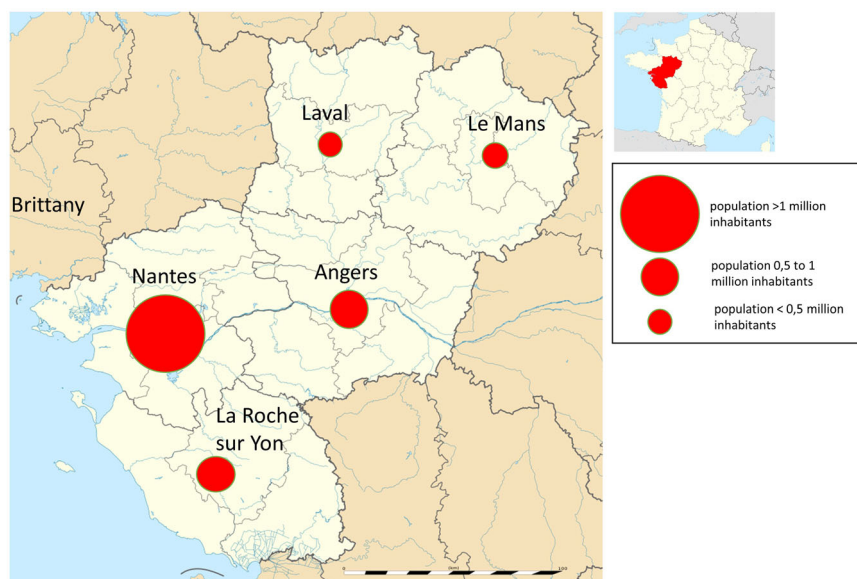
The literature on other types of call centers offers a wide range of analytical modeling methods depending on objectives and levels of

decision³⁴. Unfortunately, there is often a significant gap between these theoretical models and reality. It is for this reason that we chose to model each EMCC as a discrete event, a queued process, a more accurate approach than purely analytical methods, and configure it using empirical distributions derived from real data which are more representative than the mathematical distributions usually used³⁵. These choices enabled us to obtain highly precise estimates with very narrow 95% confidence intervals, but also with good validity as shown by the comparison of the predictions of the digital twins with the indicators actually observed during the validation phase.

Despite the advantages of this approach, it is important to note certain limitations. Firstly, while simulations can be carried out very quickly, several months of work were required to make them possible. This time was devoted to resolving regulatory and technical issues notably linked to data recovery, security and pre-processing, as well as modeling construction and calibration. This incompressible period was prolonged by the onset of the COVID-19 pandemic which had a marked impact on the availability of call centers for research (data collection, formatting and transfer) owing to the greater time needed for operational purposes, mostly granting security, and thus limiting the time personnel could devote to support research practice.

Another limitation of our approach is that it focuses on improving one key indicator: QoS₃₀, average value of QoS_{30i} (*i* = 1 to 336). In order to gain an overall view of the impact of the different organizational scenarios, other

Fig. 4 | Population distribution in the Pays de la Loire area. It presents the distribution of the population in the Pays de la Loire area and the population density for each department. The figure shows that the region is representative of France, with some areas very densely populated and others with lower densities.



indicators such as ECO occupancy rate or the call acceptance rate (ratio between calls answered and incoming calls) could have been measured. It should be noted, however, that reception rate is linked to service quality and occupancy rate is also correlated with it³⁶. Clearly, organizational changes such as those envisaged in our study cannot be effectively implemented without also assessing their acceptability by the stakeholders. For this reason, we have also carried out a qualitative evaluation based on interviews with EMCC professionals which will enable us to assess acceptability to the implementation of organizational changes.

The methodology delineated in this study is applicable across various settings but the findings may lack broad generalizability. Our investigation specifically focused on the collaborative dynamics among three distinct categories of EMCCs operating at varying activity levels. Although this structuring aligned with the local context, the implications of decompartmentalization scenarios could diverge for EMCCs with different activity levels or collaborations involving a different number of EMCCs. To achieve generalizability, a comprehensive simulation encompassing all potential combinations of EMCC types, while considering regional particularities, is imperative. It will also be necessary to carry out a study of the impact of decompartmentalization on EMCC. Our analyses were conducted during the peak week of July 12 to 18, 2021, providing insights into interconnectivity and virtualization effects during high-demand periods. These situations of high activity could constitute an excellent scenario for the potential application of decompartmentalization. Further simulations are required to evaluate different temporal contexts and the elevated activity levels seen during the COVID-19 pandemic. The week analyzed in our study, while outside a COVID-19 impact wave in France, aligns with a period of increased demand associated with the summer holiday season. However, the call volume during this period remained lower than the peak levels observed during the major COVID-19 waves of 2020 in France. Furthermore, a comprehensive cost-benefit analysis of diverse scenarios is essential to facilitate decision-makers in selecting optimal solutions. The implementation of organizational changes is facilitated by the French national SAMU modernization program. This program deploys a centralized telephony system nationwide, enabling the interconnection and/or virtualization of emergency call distribution. It also includes an exchange hub for sharing and exchanging records created within the EMCCs across the country. This initiative is regulated by the French government under the DGOS instruction DGOS/PF5/R2/2022/201 of October 10, 2022.

Integrating digital twins into call centers holds significant potential for enhancing efficiency, safety, and overall system management. The use

of digital twins in healthcare system management is an emerging field with limited but increasing presence in the literature to support its application. Digital twins are increasingly being utilized to ensure patient safety and well-being within organized systems. Future studies aiming to address healthcare system challenges and improve performance should therefore investigate the potential of digital twin technology. Furthermore, it is crucial for these technologies to embed human factors and ergonomic principles to ensure better design and a more successful impact on patient and doctor experiences³⁷. This approach will help maximize the benefits of digital twins, leading to improved healthcare outcomes and operational efficiency.

Overall, our digital twin approach to evaluating the territorial organization of medical response to emergency calls is an innovative approach in this field. It enabled us to quantify the potential impact of different decompartmentalization scenarios on QoS and will enable decision-makers to select those that are worth implementing and evaluating in real life. Other types of EMCC organization are currently being evaluated on the basis of the digital twins constructed, in particular the two-level call answer which should enable us to better illustrate the contribution of this type of approach to the organization of the care system.

Methods

Our study was based on data from three of the five EMCCs in the Pays-de-la-Loire region (France), covering 3.8 million inhabitants or 5% of the national population (Fig. 4). The three EMCCs in the study, referred to as EMCC-A, EMCC-B and EMCC-C below, have average daily volumes of incoming calls that can be classified into three broad categories representative of all French EMCC: between 1000 and 1500 calls for EMCC-A, between 500 and 1000 calls for EMCC-B, and fewer than 500 calls for EMCC-C.

The organizational hypotheses evaluated in this study were therefore based on collaboration between these three categories of EMCC. The methodology followed is based on call flow simulations performed on digital twin of incoming call reception, initial decision and referral processes in the three EMCCs. Each digital twin of each real EMCC was constructed from observations, interviews, and was powered by real production data from emergency phone calls made between January 1 and December 31, 2021, amounting to 1,200,000 calls in all. More precisely, the average number of incoming calls arriving in the three EMCCs of the study on each week of 2021 was 22,591. Since 2021 was heavily affected by COVID-19, we focused the study on the week of July 12 to 18 which turned out to be the busiest week

Fig. 5 | Overview of incoming call volume during the summer period (Monday, May 31 to Sunday, August 15, 2021). It provides an overview of the volume of incoming calls during the summer period (Monday, May 31 to Sunday, August 15, 2021) and identifies the week of highest activity considered for this study (Monday, July 12 to Sunday, July 18).

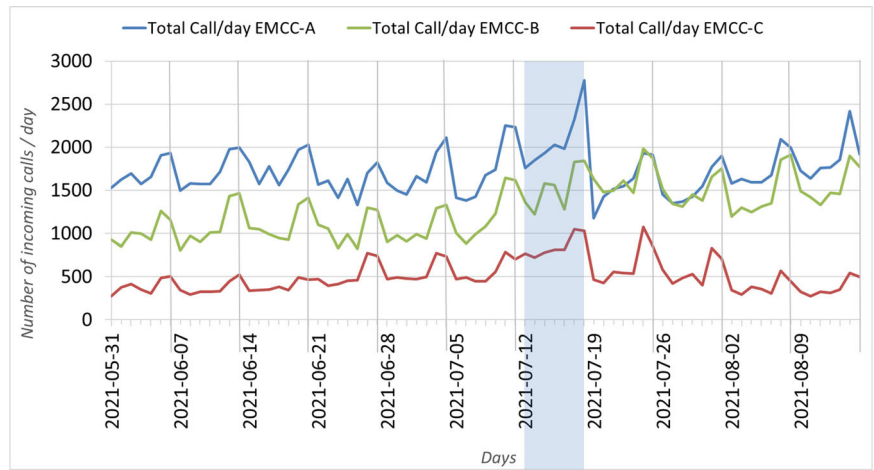


Table 4 | Overview of input and output per slot (example of EMCC-A)

Slot #	Date Time	Input data		Simulation output data			
		Nb_ECO	Nb_Incom	Nb_30sec	Nb_ALost	Nb_Answered	QoS_30i
...
18	07/14/2021 08:30	7	62	8	4	57	86%
19	07/14/2021 09:00	5	52	6	5	48	88%
20	07/14/2021 09:30	5	60	40	5	53	25%
21	07/14/2021 10:00	5	71	54	10	62	13%
22	07/14/2021 10:30	5	74	50	19	55	9%
23	07/14/2021 11:00	5	52	10	8	45	78%
24	07/14/2021 11:30	6	43	0	5	38	100%
25	07/14/2021 12:00	6	47	1	3	43	98%
26	07/14/2021 12:30	5	38	2	1	37	95%
27	07/14/2021 13:00	6	52	6	3	49	88%
28	07/14/2021 13:30	6	58	5	3	56	91%
29	07/14/2021 14:00	5	57	13	6	51	75%
...

Input data to feed the simulation are exactly the same as real production data: the [Nb_ECO] column contains the number of ECOs allocated to each slot to answer incoming calls, and the [Nb_Incom] column contains the number of incoming calls for each slot. The following columns are results output by the simulation. The [Nb_30sec] column contains the number of answered calls that took more than 30 s to answer. The [Nb_Alost] column contains the number of abandoned (within 10 s) and lost calls before to be answered. The [Nb_Answered] column contains the number of calls answered. The [QoS_30i] column is the calculation of the QoS on each 30-min slot.

of 2021 in terms of the number of calls in the three EMCCs owing to a seasonality effect (summer holidays) and the bank holidays on Wednesday July 14 which was the busiest day of the year. For this specific week, the number of incoming calls was 32,480 (+43% compared with the weekly average value). The data was collected under conditions of system stress that were also observed at other times of the year. Furthermore, the analysis of incoming calls over the year highlights a weekly periodicity that is substantially synchronous for the three EMCCs. Figure 5 focuses on 11 particularly busy weeks in summer (Monday, May 31 to Sunday, August 15). The incoming-call peaks which appear more at the end of each week (on Saturday or on Sunday) highlight this weekly periodicity. The blue zone highlights the week of highest activity considered for this study (Monday 12 to Sunday 18 of July). Whatever the week, call peaks appear on the same days at the three EMCCs, which could suggest that decompartmentalizing calls would not bring any gain since all the EMCCs seem to be simultaneously overloaded. This study will verify this by evaluating two possible decompartmentalization scenarios: (1) interconnection and (2) virtualization.

In order to conduct this simulation study, we drew inspiration from the framework proposed by Petitdémange et al. to diagnose and improve EMCC service³⁸. The methodology includes three main

phases: (1) data collection and preparation, (2) modeling and simulations, and (3) evaluation of organizational hypotheses. These three phases are presented below. In addition, existing processes were analyzed on the basis of evidence-based (or data-based) and interview-based reference methodologies³⁹.

Among the many emergency call-center performance metrics and indicators, we focused on the process-centric metric which corresponds to the main accessibility evaluation criterion: service level, or quality of service (QoS), which corresponds to the percentage of calls answered within a given time^{40,41}. The National Emergency Number Association (NENA) recommends that “90% of all 9-1-1 calls arriving at the Public Safety Answering Point (PSAP) shall be answered within 15 s. 95% of all 9-1-1 calls should be answered within 20 s⁴²”. For this study, quality of service in 30 s (QoS₃₀) was chosen as the main output measure for the simulation, as it is the main quality indicator for EMCCs in France. Its target value is 99%, i.e., 99% of calls should be answered in less than 30 s. Equation (1) was used in accordance with the recommendations for the French Health Authority (Haute Autorité de Santé) (HAS, https://www.has-sante.fr/upload/docs/application/pdf/2020-10/guide_methodologie_qualite_samu.pdf) to calculate QoS₃₀, with Nb_Answered as the

number of calls taken and Nb_30sec as the number of calls taken in more than 30 s.

$$QoS_{30} = \frac{Nb_Answered - Nb_30sec}{Nb_Answered} \tag{1}$$

For this study, the quality-of-service QoS_30i was calculated over each 30-min slot in order to analyze its variability along the week. Over one week, 336 QoS_30i values were measured (48 slots of 30 min/day over 7 days).

We computed an average value of QoS_30i over the week ($AQoS_{30}$) in order to have an overview of the quality of service along the week. Equation (2) was used to calculate $AQoS_{30}$.

$$AQoS_{30} = \frac{1}{336} \sum_{i=1}^{336} QoS_30i \tag{2}$$

Table 4 provides an overview of input and output data per 30-min slot obtained after a simulation. This extraction shows 12 slots (#18 to #29) from 8:30 to 14:00 on the French National Day (07/14/2021). For full one-day (48 slots) output data, see Supplementary Table 4.

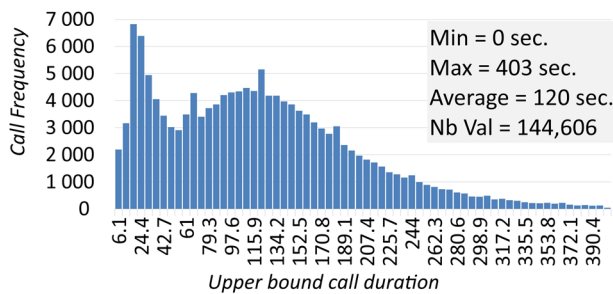


Fig. 6 | Data preparation example: distribution of call durations. It shows the frequency distribution of call duration (min and max). It is used as an input to randomly simulate the duration of each call answered.

Phase 1. Data collection and preparation

The construction of a digital twin relies on two main sources of digital data collected by an information system, each of which contains data specific to each call: (1) data from the telephony software which automatically collects all time-stamped events for each telephone call and (2) data from the medical regulation software. From the event logs that record every telephone call received in each EMCC, a data preparation algorithm obtained the data required to build the digital twin and for simulation input: probability of a call being abandoned or lost before being picked up; number of incoming, abandoned, lost, and answered calls per 30-min slot; number of ECOs allocated to each 30-min slot; time period before answer; time period before loss; time period before abandonment; duration of communication with the ECO; duration of accompaniment of each call by the ECO in medical regulation and/or completion of the regulation file. One of the main differences between digital twinning and ‘traditional’ mathematical modeling is that all of these durations were modeled in the form of empirical distributions divided into bins of identical width, highlighting the probability or number of occurrences in each of the bins. For example, Fig. 6 illustrates the distribution used as input to randomly simulate the call duration of each answered call. The average call duration was 120 s and duration ranged between 0 and 403 s. The most likely call duration (highest peak) was between 12.2 and 18.3 s. During a one-week simulation, a large number of calls were answered (between 5500 for EMCC-C and 13,500 for EMCC-A). The simulated durations are randomly drawn according to the probability associated with each bin of this empirical distribution. Supplementary Table 3, for the detailed distribution data table.

In addition, time stamping the events of each call in the real production database enabled a posteriori reconstruction of the treatment process using process mining algorithms⁴³. A process mining algorithm is able to transform data into a node-edge diagram. More precisely, data are time-stamped traces of each call (log file) and the generated node-edge diagram is a directed graph corresponding to the process model of the treatment of all of the calls^{44,45}. The merging of all instances of the process followed by each call, comparable to a queuing network, corresponds to the overall process which is then modeled in the form of a digital twin (Supplementary Fig. 1).

Phase 2. Modelling and simulations

Figure 7 shows a knowledge model of the front-office process of receiving calls by an ECO that is universally deployed in all emergency call centers.

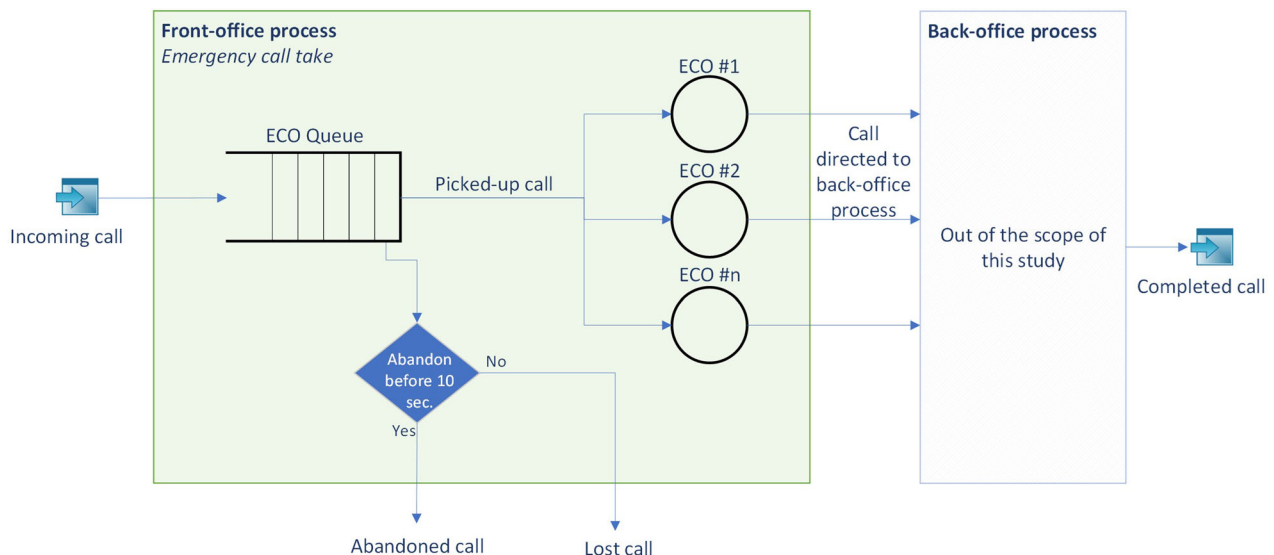


Fig. 7 | Knowledge model of the front-office process. Knowledge model of the process of receiving calls by an emergency call operator (ECO) that is universally deployed in emergency call centers. Incoming calls arrive in the ECO queue. Some callers leave the queue before being connected to an ECO, in two categories: (1)

abandoned calls leave the queue within 10 s and (2) lost calls leave the queue after 10 s. In addition to abandoned and lost calls, calls in the queue are handled by the first available ECO on a first-in, first-out (FIFO) basis. The regulation process focused strictly on the front-office process.

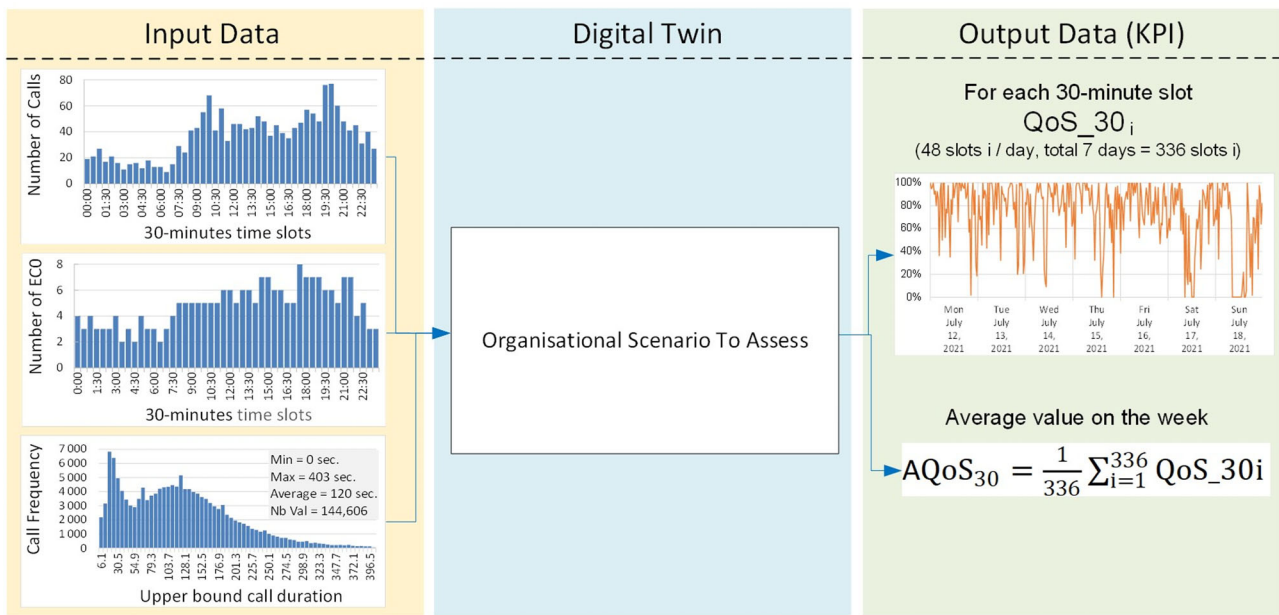


Fig. 8 | Overview of the Digital Twin developed with Witness. It provides an overview of the generic digital twin front-office process of a call center with its input data (on the left) and output responses (on the right: QoS₃₀ for each 30-min slot *i*, and the average value AQoS₃₀) according to the organizational scenario to be tested. Three main input data that are extracted from the real production database are: (1) the number of incoming calls in each 30-min slot (top-left diagram); (2) the number of operators ECO scheduled in each 30-min slot (middle-left diagram); (3) the call duration distribution. The digital model (in the center of Fig. 8) is powered by these

input data during a simulation run on the 7 days of the studied week. At the end of a simulation run, two main output data are collected: (1) the value of QoS₃₀ in each 30-min slot enabling analysis of the variability of the QoS in the week (orange curve on the top-right diagram of Fig. 8). To quantify this variability, the coefficient of variation (CoV % = 100 * Standard Deviation / Mean) is calculated. The larger the CoV, the more QoS₃₀ is spread out; (2) The average value of QoS₃₀ is calculated in the 336 30-min slots of the week (bottom-right equation in Fig. 8). This figure is enlarged and split into five figures in Supplementary Figs. 2 to 7.

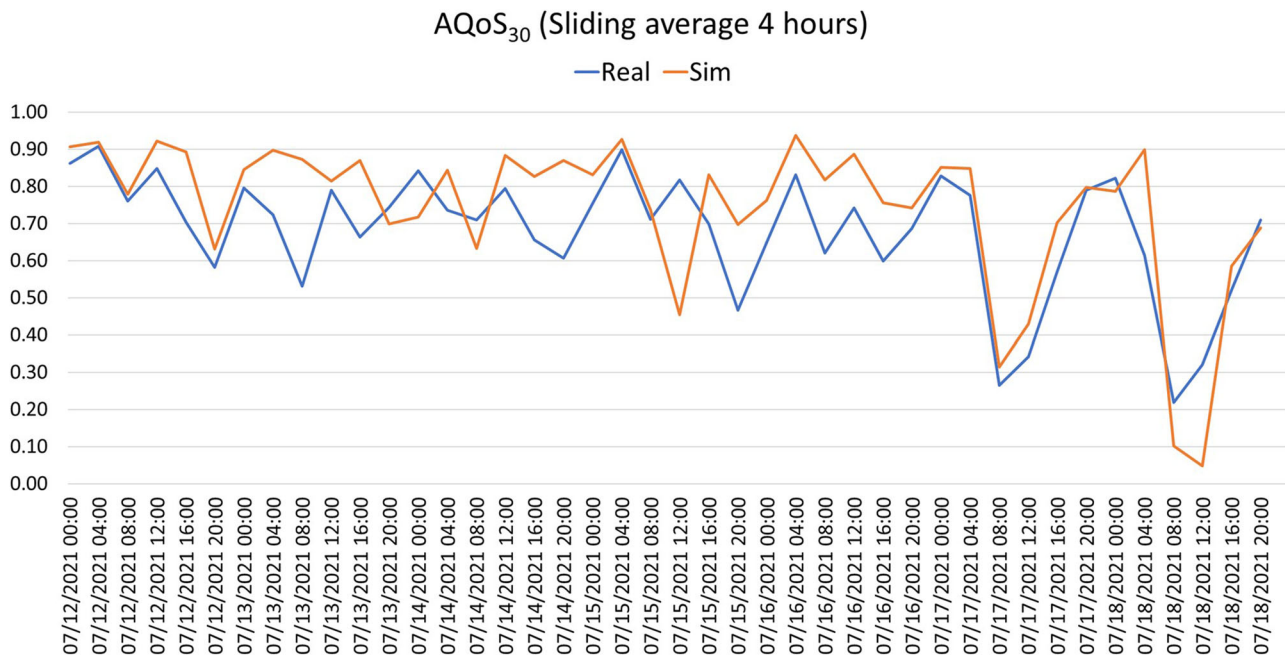


Fig. 9 | Comparison between real data (blue line) and simulated data (orange line). It shows the comparison of real and simulated values of AQoS₃₀ for the EMCC-A in the existing organization (partitioned). The mean signed deviation between

real and simulation data was equal to 7% for this example and the simulated line (orange) logically follows the same developments as the real line (blue). We considered that the behavior of the digital twin was close to the behavior of its real-world twin.

Incoming calls arrive in the ECO queue. Some callers leave the queue before being connected to an ECO according to two categories: (1) abandoned calls leave the queue within 10 s and (2) lost calls leave the queue after 10 s. Abandoned calls can be considered as dialing errors, but lost calls

correspond to too-long-waiting time for the callers. Apart from abandoned and lost, the calls in the queue are answered by the first available ECO according to a first-in-first-out (FIFO) rule. The medical call regulation process (back-office) is outside the scope of this study since we only sought

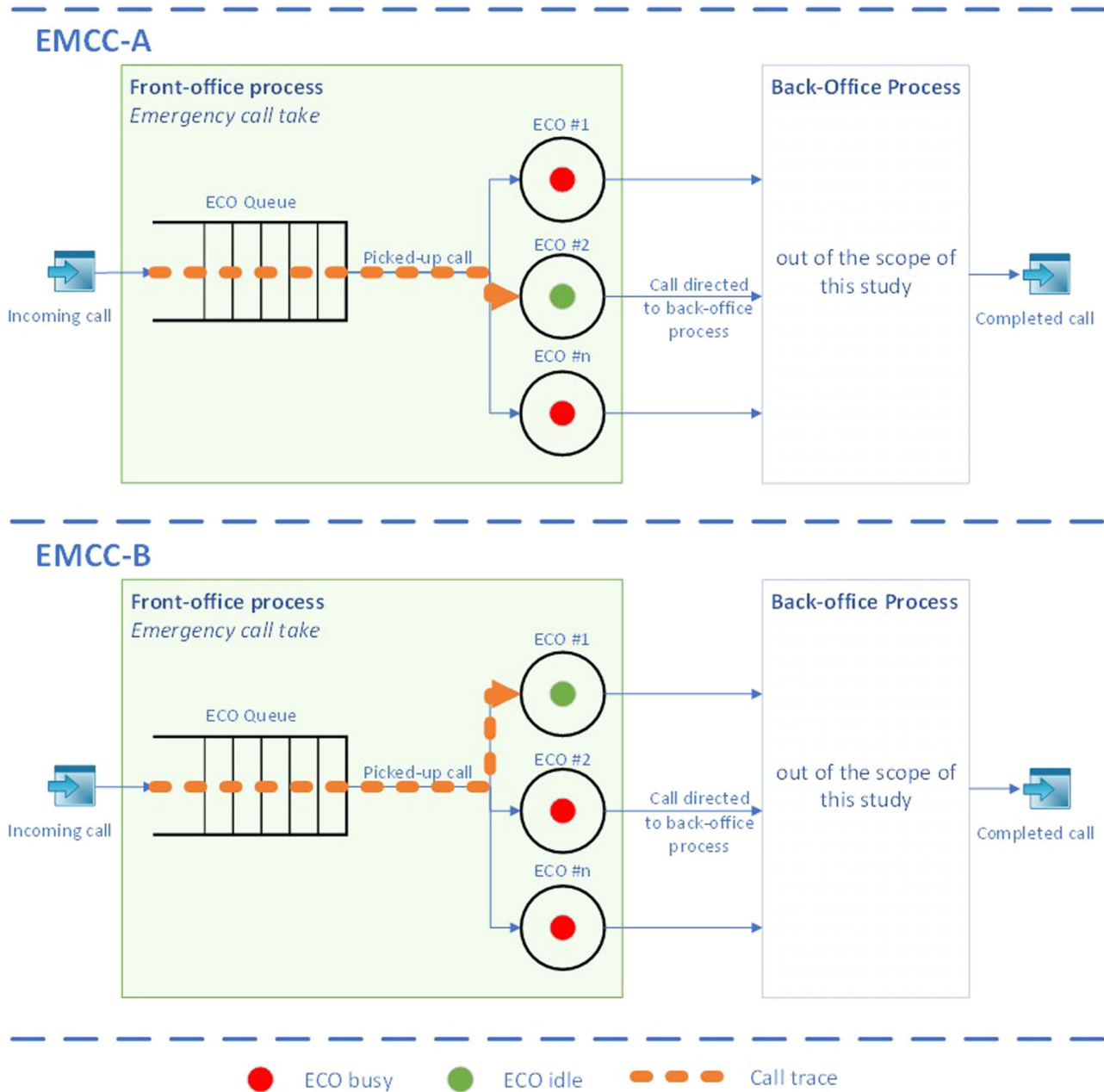


Fig. 10 | Scenario 1: Example of two partitioned EMCCs (EMCC-A and EMCC-B). It shows the partitioned organization, which means that there is no interoperability between the EMCCs. It forces each EMCC to handle only incoming calls routed from its own geographical territory. This scenario corresponds to the existing organization.

to evaluate the accessibility of call centers to the population. Our interest was therefore centered on the front-office process.

Based on this knowledge model and the data obtained in the first phase, a digital twin of each EMCC’s front-office process was developed using discrete-event simulation software (Witness™, <https://www.lanner.com>). The modeling environment for this simulator has three main building blocks: (1) entities to model incoming calls (“incoming call” in Fig. 7); (2) buffers to model queues (“ECO queue” in Fig. 7); and finally (3) processors to model call processing activities by ECOs (ECO #1 to #n in Fig. 7).

Figure 8 provides an overview of the generic digital twin front-office process of a call center with its input data (on the left) and output responses (on the right: QoS_{30i} for each 30-min slot *i*, and the average value AQoS₃₀) according to the organizational scenario to be tested (Supplementary Figs. 2 to 7). Three main input data that are extracted from the real production database are: (1) the number of incoming calls in each 30-min slot (top-left diagram); (2) the number of

operators ECO scheduled in each 30-min slot (middle-left diagram); (3) the call duration distribution (previously described and detailed in Fig. 6). The digital model (in the center of Fig. 8) is powered by these input data during a simulation run on the 7 days of the studied week. At the end of a simulation run, two main output data are collected: (1) the value of QoS_{30i} in each 30-min slot enabling analysis of the variability of the QoS in the week (orange curve on the top-right diagram of Fig. 8). To quantify this variability, the coefficient of variation (CoV% = 100 * Standard Deviation / Mean) is calculated. The larger the CoV, the more QoS_{30i} is spread out; (2) The average value of QoS_{30i} is calculated in the 336 30-min slots of the week (bottom-right equation in Fig. 8).

Each digital twin, a virtual replica of each EMCC, was built and validated in successive iterations. For this purpose, the “black box” validation method presented by Robinson was applied¹⁶. The validation option chosen was to check whether a similar evolution on an input parameter of an EMCC

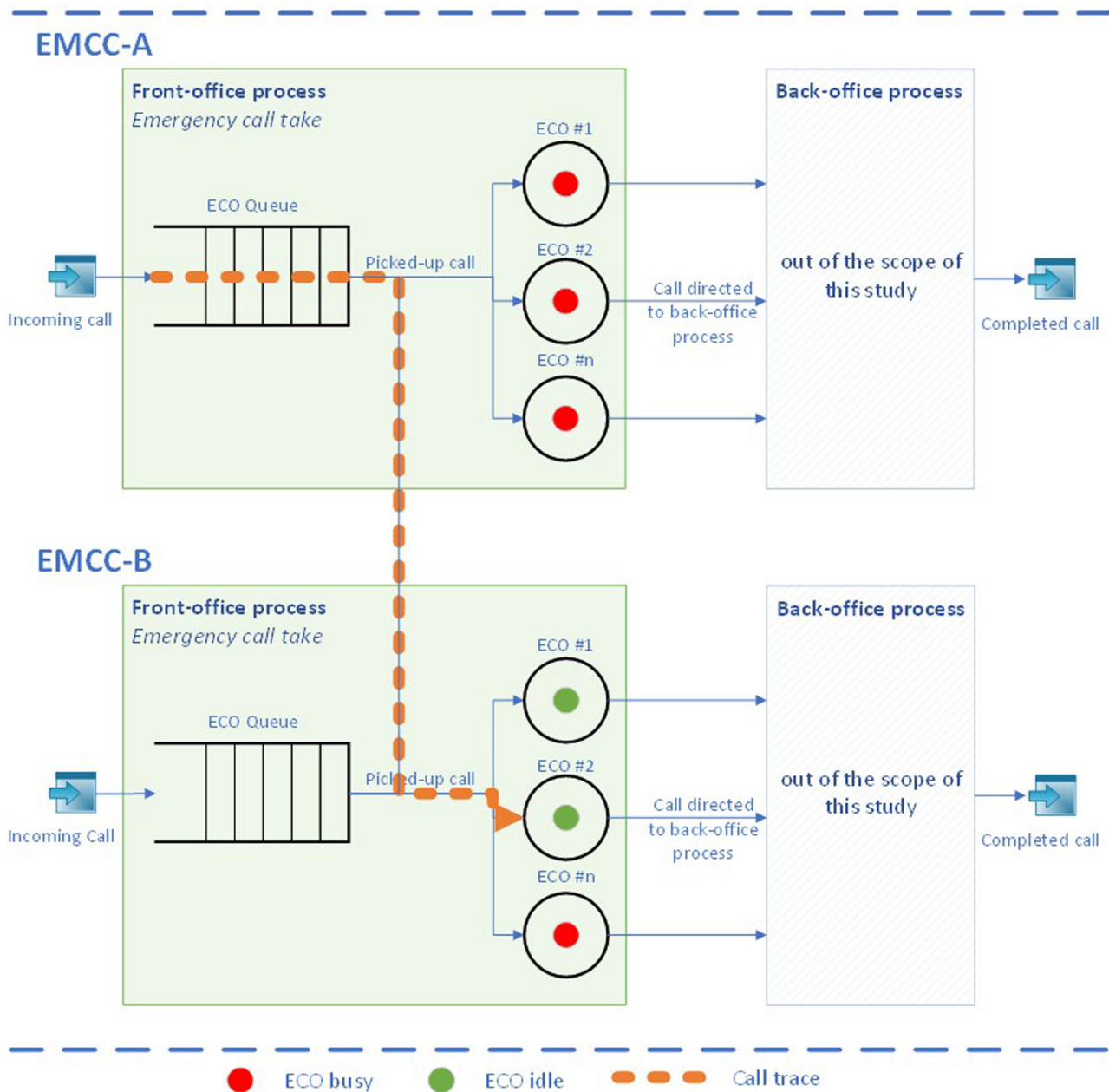


Fig. 11 | Scenario 2: Example of two interconnected EMCCs (EMCC-A and EMCC-B). It illustrates the interconnected organization. Each EMCC retains its own queue of calls arriving from its geographical territory. However, an ECO can, if available and if there are no calls in his or her own queue, pick up calls from the queue of another EMCC.

and its digital twin produce the same evolution of a selected output response. For example, if we consider two real days (d1 and d2) in a given EMCC for which a change in the number of ECOs and in the number of incoming calls resulted in a decrease in quality of service, similar changes in the digital twin of this EMCC should result in the same trend. However, due to random distributions and probabilities for a call to be abandoned, lost, or answered, the time-stamped sequence output by the digital twin cannot exactly match the observed data. To validate the behavior of the digital twin during the studied week, we, therefore, compared the averages of the real and simulated values of QoS_{30i} calculated on 42 successive sliding periods of 4 h. For example, Fig. 9 shows the comparison of real and simulated values of $AQoS_{30}$ for the EMCC-A in the existing organization (partitioned). The mean signed deviation between real and simulation data was equal to 7% for this example and the simulated line (orange) logically follows the same developments as the real line (blue). We considered that the behavior of the digital twin was close to the behavior of its real-world twin.

According to the confidence interval method proposed by Robinson⁴⁶, we needed to run at least five replications of each scenario to obtain a deviation of less than 1% of the 95% confidence interval around the cumulative mean of $AQoS_{30}$, which shows that the duration of each replication is large enough to obtain statistically representative results. Finally, we decided to run 10 replications for each scenario, which showed that the confidence interval of $AQoS_{30}$ did not exceed 2% for any of them.

The simulation of a week's activity takes just over 2 min or ~20 s per day on an intel Core i7 computer with 2.6 GHz and 52 GB RAM. QoS_{30i} values were obtained for each 30-min slot i , i.e., 336 slots (i.e., 336 QoS_{30i} values, for $i = 1$ to 336) for the week.

Phase 3. Evaluation of organizational hypotheses

Three different organization scenarios were simulated and evaluated: (1) a partitioned organization (the existing organization) without collaboration,

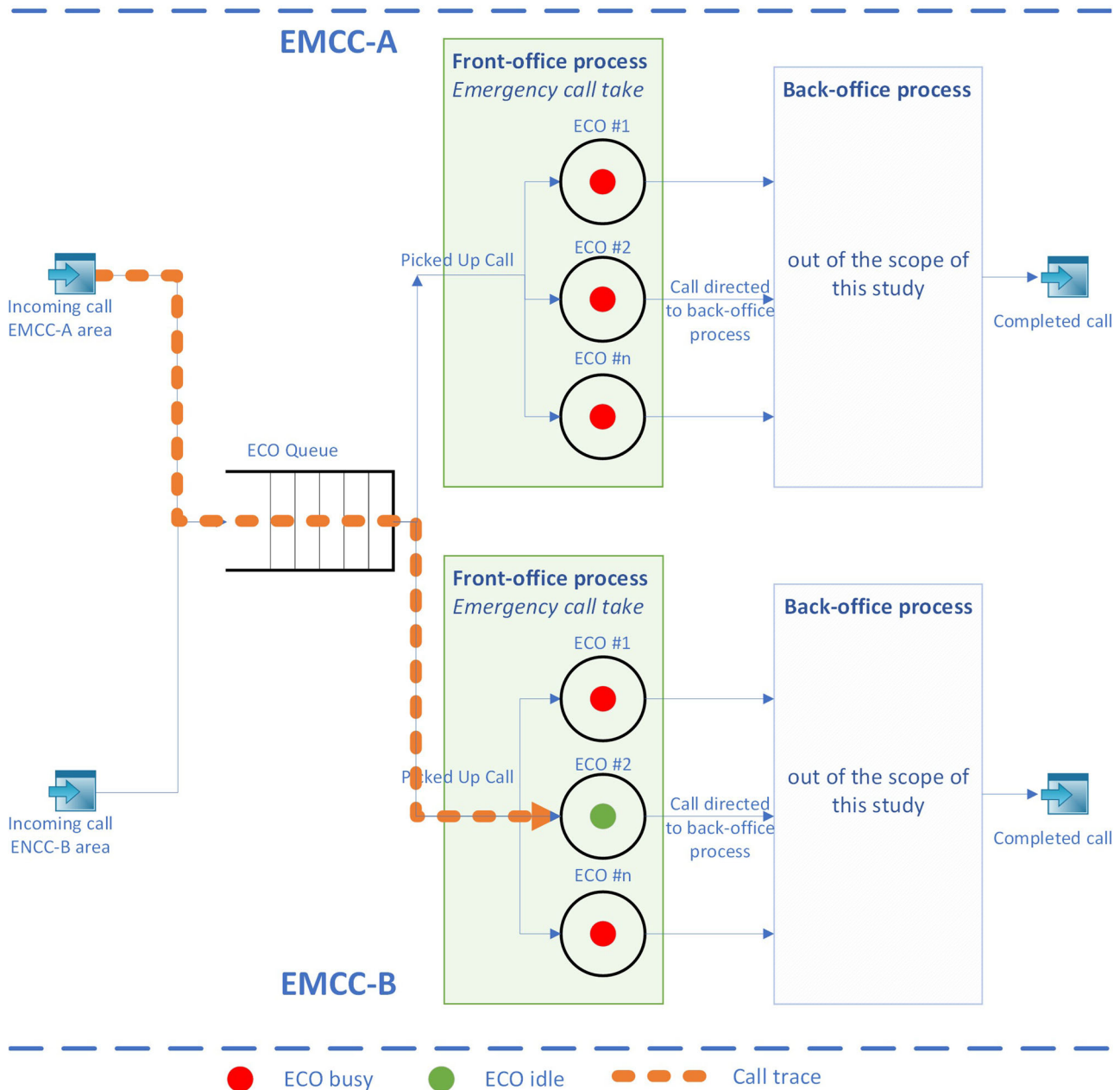


Fig. 12 | Scenario 3: Example of two virtualized EMCC (EMCC-A and EMCC-B). It shows the virtualized organization. In this case, it is with a single queue common to all centers. A call in this queue is picked up on a first-in-first-out (FIFO) basis by the first available ECO from any EMCC.

(2) an interconnected organization, and (3) a virtualized organization, both of which allowed collaboration.

Scenario #1: Partitioned organization (Fig. 10)

Partitioned organization means no interoperability between EMCCs. It forces each EMCC to handle only incoming calls routed from its own geographical territory. In the event of a one-off overflow, an EMCC can only rely on its own resources which often has the effect of impacting call pick-up times owing to excessive resource occupancy. This scenario corresponds to the existing organization.

Scenario #2: Organization in interconnected mode (Fig. 11)

In this mode, each EMCC retains its own queue of calls arriving from its geographical territory. However, an ECO can, if available and if there are no calls in his or her own queue, pick up calls from the queue of another EMCC (orange dotted arrow in Fig. 11).

Scenario #3: Organization in virtualized mode (Fig. 12)

Like the previous one, the aim of this mode is to decompartmentalize the EMCCs. However, in this case, it is with a single queue common to all centers. A call in this queue is picked up on a FIFO basis by the first available ECO from any EMCC (orange dotted arrow in Fig. 12).

For Scenarios #2 and #3, ECOs remain assigned to their EMCC with a constant workforce and work schedule similar to the existing as-is configuration.

Data availability

Raw data were generated at CHU Nantes. Derived data supporting the findings of this study are available from the corresponding author on reasonable request.

Code availability

The underlying code for this study [and training/validation datasets] is not publicly available but may be made available to qualified researchers on reasonable request from the corresponding author.

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Author contributions

Y.P., F.F., and B.L. conceived the study. J.J., D.S., V.D., F.D., and A.B. accepted to collaborate in the study and gave access to the data. C.M., N.C., C.P., and FF extracted the data and built the database. B.L., F.F., N.C., C.P., Y.P. analyzed the database. F.F., N.C., and C.P. produced the analysis results. Y.P., N.C., C.P., and F.F. directly accessed and verified the underlying data reported in the manuscript. Y.P., F.F., B.L., and E.M. wrote the manuscript. All other authors, Y.P., C.M., N.C., C.P., J.J., D.S., V.D., F.D., A.B., Q.L.B., E.M., B.L., F.F. have made major critical revisions and give

written permission for publication of the manuscript and any unpublished material cited in the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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