Process stress in municipal wastewater treatment processes: a new model for monitoring resilience

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Abstract

Although not-well-understood, process stress could provide a novel approach to resilience analyses in wastewater treatment processes by identifying the influence of a stressor on wastewater processes. This paper identifies how industry and academia view the concept of process stress in wastewater treatment processes. It also investigates how individuals, their role and education influence their decision bias and their propensity to use decision support tools. Survey results from 255 respondents showed that many wastewater professionals still have a preference to use personal or company-specific spreadsheets (33%), with a similar proportion of respondents using simulation and decision support tools (29%). The concept of process stress in wastewater treatment was well understood by industry and

academic professionals as a variance from benchmarked conditions. This analogy of process stress means that it can be either, a positive or negative magnitude of variation from a benchmarked state, which expands on the approach taken in current resilience and benchmark simulation models. Therefore, the concept of process stress was a well understood by a vast majority of respondents, with 82% of respondents agreeing that an analytical tool that considers process stress would be a useful contribution to developing the understanding and management of process resilience. The study also highlights the requirement for a process stress analysis methodology, which builds on current resilience methods and separates the stressor (cause) from process stress (effect). Overall, this research has identified the requirement to measure and analyse stresses in wastewater treatment processes and recommends a strategy to develop this methodology.

Keywords

Resilience, Wastewater Process Stress analysis, Benchmark, Wastewater process analysis, EDSS, Process Modelling

1. Introduction

Water supply stress is apparent in many parts of the World. However by 2100 the predicted increases in human population (47% increase) and global temperatures (2^{o}C > pre-industrial levels) will exacerbate stress to both supply and wastewater treatment (Walker, 2016). These stresses will be manifested by an increase in high-intensity rainfall (12-24%) and extended dry periods (Fischer, Sedláček, Hawkins, & Knutti, 2014; Hansen, Ruedy, Sato, & Lo, 2010). Consequently, wastewaters will be highly concentrated during dry weather and dilute during heavy precipitation (The Met Office, 2018) subjecting existing wastewater treatment processes to environmentally generated stress in addition to growing populations. Without adequate monitoring methodologies, future generations will be subject to serious pollution incidents and lack of compliance with treatment standards (Europa, 1991, 2000). Therefore understanding how different processes in existing wastewater treatment trains respond to these stresses in will play a crucial role in adapting to climate change and population growth.

Wastewater treatment plants are complex systems receiving variable flows and loads, which typically pass through a series of unit processes with different physical, chemical and biological treatment mechanisms. Simulations have been developed at a plant-wide scale, which captures the complexity of wastewater process perturbations. Some examples of simulation based software packages are BioWin, West (Mike) and GPS-X (Hydromantis), which use fixed, and dynamic flow and load simulations to replicate real life scenarios. These simulations have showed a close correlation to the real performance of well monitored wastewater process streams (Mike DHI, 2018; Nghiem, Wickham, & Ohandja, 2017). Although, simulations can accurately replicate the outcomes of real wastewater treatment processes, the calibration of such sophisticated models requires specialist knowledge, additional process samples and can be time consuming if a high level of accuracy is required. Therefore, in an industrial context, where operational labour and wastewater treatment plant management staff require a rapid overview of plant performance, plant-wide models may be unsuitable unless prior calibration of a selected model is performed.

Process stress is proposed as a novel concept for reckoning the complex interaction of processes in wastewater treatment plants react to external challenges to provide a relatively quick and visual management information tool. In other fields efforts have been made to understand the concept of stress and its consequences. For example, in microbiology, microbial stresses have been analysed to measure how microbes, particularly bacteria, respond to environmental challenges with varying levels of success (Han & Cui, 2016; M. Wang, Faber, & Chen, 2017; Whalen & Tracey, 2006). In wastewater the application of microbial stress monitoring has mainly focussed on the measurement of soluble microbial products, such as adenosine triphosphate, released in activated sludge (Aqua-tools, 2008; Norman, Peter., Tramble, 2017; Norman & Walter, 2011). An example of this is the work of Shi *et al*. (2017), which features the speciation of soluble microbial products for the prediction of stressful microbiological events in activated sludge. These diagnostic methods are potentially sophisticated but, as they are in their infancy, suffer from a lack of standard analytical techniques. Therefore, significant investment is required before they can be widely applied as a robust diagnostic method for biological wastewater treatment (Wang and Zhang, 2010). This highlights the requirement for a robust approach that considers stresses using pre-existing models to examine the stresses across a variety of flows and loading conditions.

Ecological stresses have also been investigated, for example Han, (2016) developed an integrated stress index to combine a variety of environmental stressors and their influence on the concentration of macrophytes in ponds. This simple heuristic method uses the sum of squares for a variety of human activities to capture the holistic impact of stress on ecological systems. Although applicable to such relatively simple ecological systems, individual contributions to stress are not resolved and, therefore, this may not appropriate for wastewater processes due to the level of complexity. Similarly, Nilsalab (2017) looked at the logistic relationship between water availability and withdrawal from freshwater supplies, with over-abstraction defined as water stress. This type of stress occurs when the abstraction of freshwater exceeds the total water availability and is performed at macro-scale, with many observations becoming generalisations of independent variables. In summary, both of these methods may be appropriate for relatively simple environmental systems they lack the complexity to model the many biochemical and physical/chemical interactions present in wastewater treatment processes.

The role of wastewater process engineers is to evaluate the performance of existing wastewater processes based on flow and load studies, using expert judgement and manual data manipulations. However, due to the complexity of the interactions between flow and contaminant concentrations in existing wastewater processes stresses can be difficult to interpret manually and operational decisions are often based on expert judgement (Kimberly Solon *et al.*, 2015). Although many of the parameters and models are better understood with the use of plant-wide and extended plant-wide models, calibration is key to avoiding unexpected results (Fernández-Arévalo, Lizarralde, Grau, & Ayesa, 2014; K Solon et al., 2017). More commonly water utilities view stressors as the risk of certain events causing a catastrophic failure or pollution incident (ch2m & Ofwat, 2017). This relationship between risk and wastewater process stress has been explored in the research of Comas (2008) where scenario-based, risk assessments are used to evaluate rising sludge control methodologies for activated sludge plants (Dalmau, Rodriguez-Roda, Steyer, & Comas, 2006). The main limitation of risk assessment methods is that they are often a simplification of more complex process scenarios and are limited to heuristic problems using existing knowledge (Ebrahimi, Gerber, and Rockaway, 2017). It therefore limits their application to the exploitation of existing knowledge, rather than more sophisticated knowledge discovery methods (Bagheri, Mirbagheri, Bagheri, & Kamarkhani, 2015).

To characterise stresses in whole wastewater process plants, Butler *et al.*, (2016) introduced the concept of 'Middle States', where a stress-strain plot can be used to present the available resilience. The work performed focusses on failure modes and the evaluation of a variety of interventions for wastewater process risk mitigation (Butler *et al*, 2016). Rather than focusing on individual wastewater treatment processes and where a process problem might occur, the work concentrates on how stressors influence the performance of a whole treatment plant. This impact of a stressor is termed as resilience or the reserve capacity in an entire treatment process as shown in Fig. **1**. Global Resilience Analysis (GRA) is the study of event-based stressors and their influence on the performance of a whole wastewater treatment system. As part of the GRA discrete processes are not considered, with analysis reliant on the original operating conditions being measurable. A significant source of uncertainty in resilience methods is that a reliable baseline can be challenging to measure due to data availability and quality. This was highlighted by Mbamba *et al*. (2016) when considering the critical data required to calibrate plant-wide phosphorus modelling for seasonal and diurnal variations.

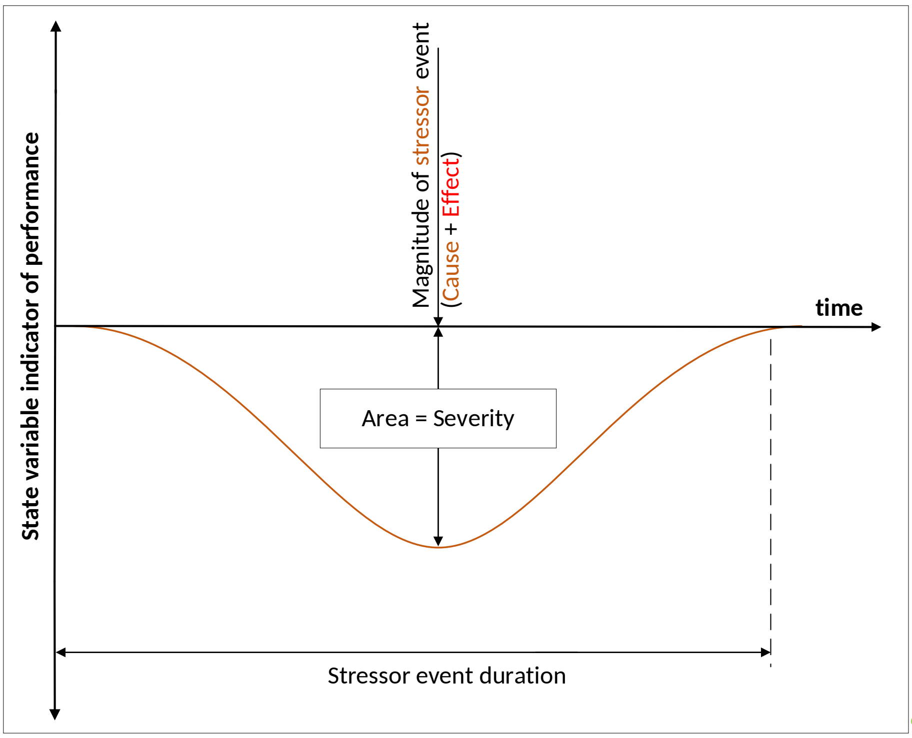

***Fig. 1** Resilience analysis presented by* Juan-García (2017), *adapted from* Mugume (2015)**.**

Resilience theory has been successfully applied to whole wastewater treatment systems and researchers such as Juan-García *et al.* (2017) discuss the influence of stressors on a process response curve. Therefore resilience in a whole wastewater treatment system is linked to the internal response of a plant to a stressor, which encompasses, both the cause (stressor) and effect (process stress). Other important characteristics of the stressor event curve shown in Fig. **1** is the event magnitude and system recovery time (Sweetapple, Fu, Farmani, & Butler, 2019). The main limitation of the method provided by Mugume *et al.*, (2015), is that the perceived stressor combines two parameters; 1) is the cause and relates to the characteristics of the stressor event (flow, load or toxicity); 2) is the effect and is the stress exhibited by the process (process stress). In summary, resilience theory provides an excellent overview of resilience in whole wastewater treatment plants. However, it fails to identify process problems in individual treatment processes; thus making it difficult to identify and predict failures and isolate corrective actions (Sukias, Park, Stott, & Tanner, 2018; Sweetapple *et al.*, 2019). Hence, understanding of process stress will supplement GRA and increase the accuracy of analysis.

To expand the understanding of resilience and show that simulation, diagnostics, control and analytics are not mutually exclusive of one another. Fig. **2** was constructed to show the interaction of the four independent parameters (simulation, diagnostics, control, and analytics) and the position of process stress and resilience analyses. Therefore, resilience combines diagnostics and analytics to provide control interventions, which are then evaluated. Process stress analysis differs as it has the potential to use diagnostics and analysis to simulate a stress response from a discrete wastewater processes in a relatively simple calculation.

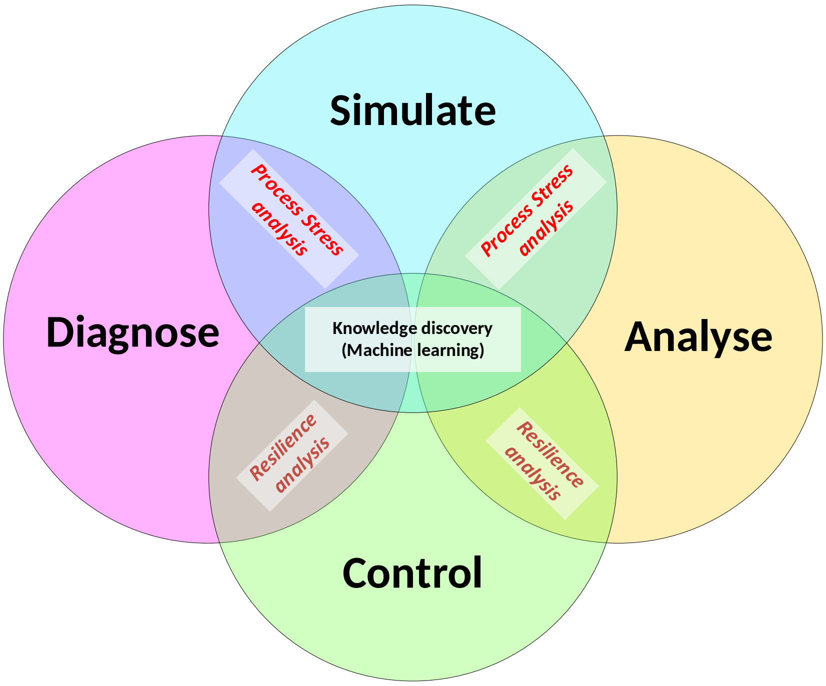

Fig. 2 *Process stress, resilience analysis and knowledge discovery in existing wastewater treatment processes Venn diagram.*

These approaches can provide analytical decision support for wastewater management. However despite much research into this field Corominas *et al.* (2018) found that only 16% of academic publications have led to a commercially available product. Furthermore, this work also identified limited use of statistical and machine learning methodologies to analyse a multitude of independent variables involved in modelling wastewater treatment processes (Bagheri *et al*., 2015). Therefore, the application of process stress analysis in Fig. **2** could bridge the gap to enable more sophisticated methods to understand the influence a stressor (cause) and the process stress (effect). Engagement with industry in this development would expand understanding of the importance of measuring process stress and it's application to existing processes.

This research aims to evaluate the conceptual understanding of wastewater process stress from international experts across a range of wastewater process-related disciplines. It seeks to provide, both an industrial and academic perspective, via an online survey completed between February and April 2019. The survey focused on six areas, 1) participant experience and role specifics, 2) decision support systems and their use, 3) analytical software applications and their use, 4) professional decision analysis, 5) benchmarking and process stress interpretation 6) dissemination of survey. The numerical data is presented as descriptive statistics, with coded qualitative data used to display commonalities in opinion and provide a convergence of the mixed-methods study.

2. Materials and methods

2.1. Data collection and survey design

Process stress in wastewater treatment processes is a new concept for both industry professionals and academics. It is therefore essential to understand current methods of analysis for existing wastewater treatment processes and to provide insight into the depth of professional knowledge. Therefore, a focussed epistemological survey was designed to capture the extent of current knowledge while evaluating existing analytical tools. The study used a mixed-methods approach to understand process stress in the wastewater process industry and academia. As shown in Fig. **3**, a pragmatist research philosophy was adopted to; firstly introduce the concept of process stress (qualitative) and secondly, group and rank collected data to analyse respondent responses (quantitative). Both qualitative and quantitative was then converged to capture a holistic understanding of process stress in wastewater treatment processes (Bazely, 2018).

In the first part of the survey, participants were asked to state their role and level of education. During data processing results were quantitised to give a specific ranking, using values between one and five (Driscoll *et al.*, 2007), with one the lowest level (e.g. Secondary school) through to five (e.g. Ph.D./EngD). Dichotomous, closed questions were used to capture the proportions of respondents using decision support tools and whether process stress analysis for wastewater treatment processes is a valid prospect (Creswell and Clarke, 2011). Multiple-choice questions were used to group and categorise data, particularly when identifying participants professional specialism and their industrial sector. Qualitative questions were used to add clarity to the quantitative data and codings. One example is when considering the limitations of analytical software packages, where respondents were asked to provide an opinion based statement and concept of process stress was introduced (Qualitative).

2.2 Sampling strategy experimental design

The study aimed to sample a cross section of international wastewater experts from industry and academia. Therefore a broad approach was taken to recruitment to access as wide a cross section as possible. This included links and requests for participants being sent to professional social media platforms (e.g. ResearchGate and LinkedIn groups) wastewater industry-specific websites and blogs, direct contacts were also made to consultants and engineering professional listed in directories (e.g. CIWEM), and finally direct expert and snowball sampling was used based on lists of contacts of the research team with requests to forward to potentially interested respondents.

The flow diagram in Fig. **3** shows the experimental design used in this research, with each phase indicated on the right-hand side. The first phase shows the basis for survey design and the targeted respondents for the survey. The second phase has been divided into six sections: 1) ‘experience and role specifics’, which covers industry, specialism, level of present role and qualification level; 2) ‘decision support systems’ which explores the types of decision support systems used (DSS) and whether it is a commercial product; 3) ‘analytical software application information', which examines the kind of analytical software application used, its strengths and limitations; 4) 'decision type', which considers the type of and level of the decision made; 5) 'benchmark and process stress', which explores the understanding of the term benchmark and process stress; 6) 'dissemination', which looks at the relevance of process stress and any preferences in visual presentation. By and large phase two is used to process qualitative and quantitative data, using mixed methods to rank (quantitise), code and provide a thematic evaluation of qualitative data. Phase three converged the qualitative and quantitative data using descriptive statistics via Minitab® 17 (Version 17.3.1) to show the key converged observations. Phase four extracted the key themes from the survey (qualitative and quantitative) to produce a narrative of results. Finally, Phase five summarises research outputs and the impact on future research direction.

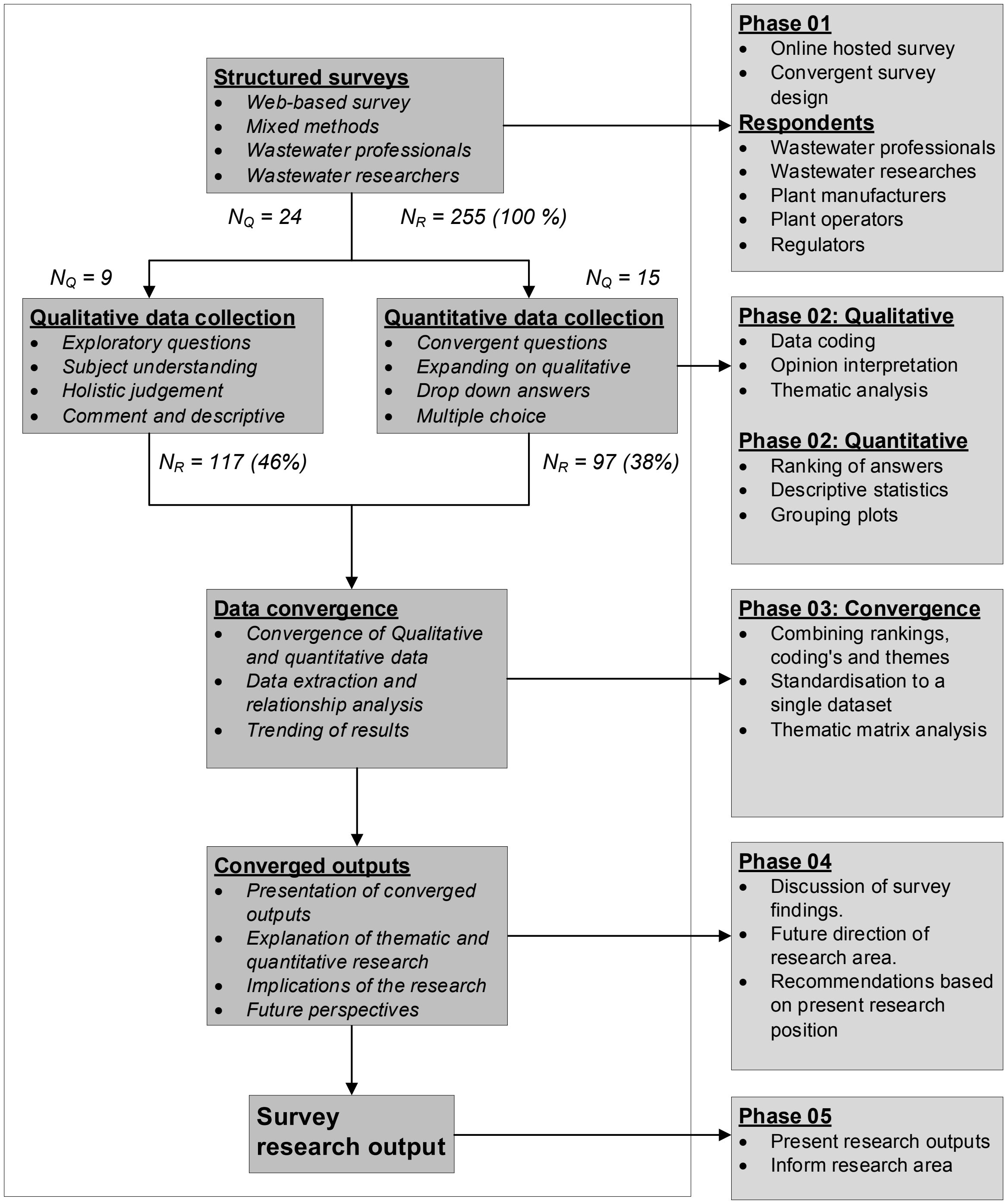

Fig. 3 *Convergent, mixed methods survey design and flow diagram. Showing the five phases of data collection, analysis and measurable research outputs. Where n_Q is the number of questions and n_R the number of respondents at each stage.*

2.3 Survey Response

The total number of responses was 290. Data screening and consolidation involved removing blank surveys (*n=13*), respondents using the survey for speculative marketing purposes (*n=9*), respondents that filled in < 10% of the survey (*n=18*) and those declining to proceed to the survey (*n=5*). After the data screening and consolidation, 255 valid completed surveys were taken forward for analysis.

3. Results and discussion

3.1 Process stress in wastewater treatment processes survey demographic

This section explores the demographic and industry sector of respondents that completed the Process Stress in Wastewater Treatment processes survey. The pie chart in Fig. 4 shows the regional zones of respondents and the proportion that completed the survey. It shows the global interest of the survey and process stress, with respondents from 43 countries and 13 regional zones. The most significant contributor to the survey was the UK, occupying 32% (*n=82*) of the total sampled population and was followed by the USA & Canada, with 32% (*n=81)*. Therefore, the most substantial survey contribution came from the developed world (Walker, 2016). Interestingly though the third-largest contributor was Central Asia, with 11% (*n = 28*), from all countries and territories eligible to receive official development assistance (OECD, 2019) . Therefore, developing countries are now showing a greater interest in sanitation and the management of wastewater treatment processes, which corresponds with the work of Gallego-Schmid, (2019), who performed a lifecycle assessment of wastewater treatment in developing countries.

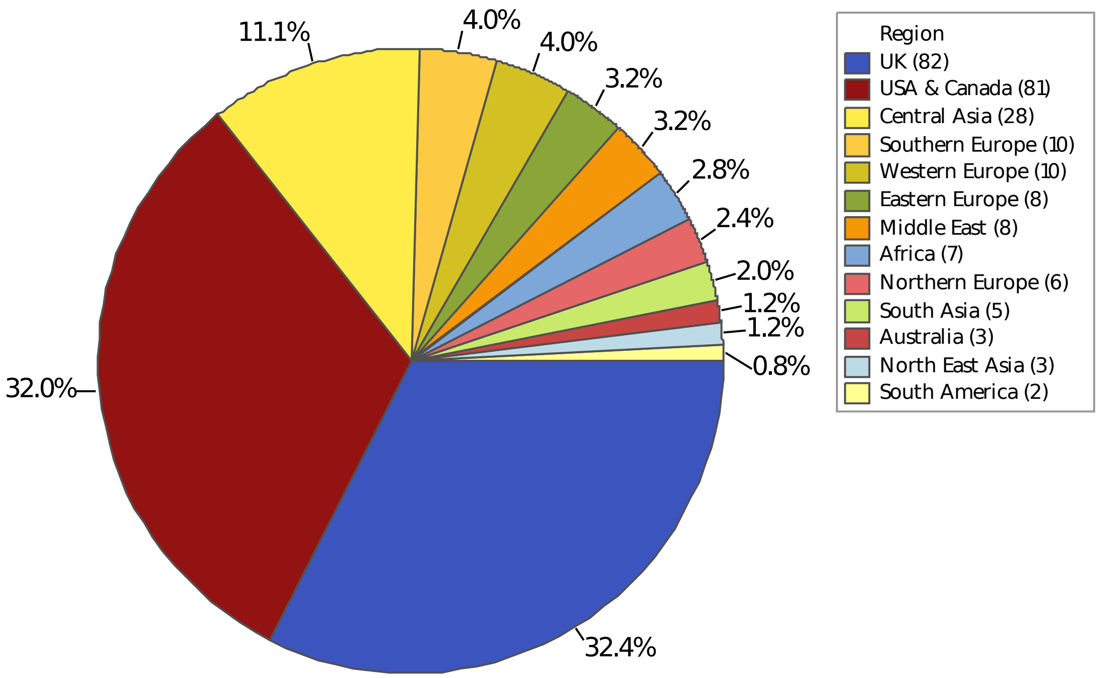

Fig. 4*. Pie chart showing survey respondents by region. Slices show the proportion of respondents that completed the survey in a particular region, with the number of respondents (n) shown in the legend, next to the regional zone in brackets.*

The pie charts in Fig. 5a and Fig. **5**b show the percentage of respondents by industry and specialism. The largest respondent industrial contribution was from Water Utilities, with 42% (*n=108*). This, in turn, explains the large contribution of operations in Fig. 5b (24.9%). Academia followed Water Utilities with 23% (*n=59*), which is thought to explain the contribution of Research and Development and Scientific shown in Fig. **5**b. Consultants were the third-largest contributor, with 17% (*n=43*) of the respondent population, followed by manufacturing with 17% (*n=27*). Therefore, although the results show a bias towards Water Utilities, it also captures a wide variety of industries to provide a holistic population. An interesting observation, which extends the study beyond existing literature, is that there is a good number of respondents from wastewater equipment Manufacturers 10% (*n=27*). This closes the loop, in that it provides a respondent population covering those working from wastewater process conception (research), through design (manufacturing), installation and on-site operation.

As shown in Fig. 5b, the area of specialism shows a range of disciplines, with the largest respondent population represented by operations with 24% (*n=63*). This was closely followed by Engineering Process with 20% (*n=52*). The sizeable operational input to the survey is unique because, operational staff are rarely consulted, but hold much empirical knowledge, which is not well covered in the literature. This observation is significant because operational staff and their maintenance routines have a considerable impact on the quality of wastewater process outputs (Serdarevic & Dzubur, 2019). One example of a method which presently excludes operational staff costs is the IWA/COST Operational Cost Index (OCI), which focusses on direct operational costs, such as energy, sludge disposal costs and external chemical addition (Copp, Jeppsson, & Vanrolleghem, 2008). Therefore, this research includes input from commonly under-represented operational staff who have a valuable empirical understanding of wastewater treatment processes. The third-largest respondent population was Research and Development, with 11% (*n=28*) and Scientific, with 10% (*n=24*).

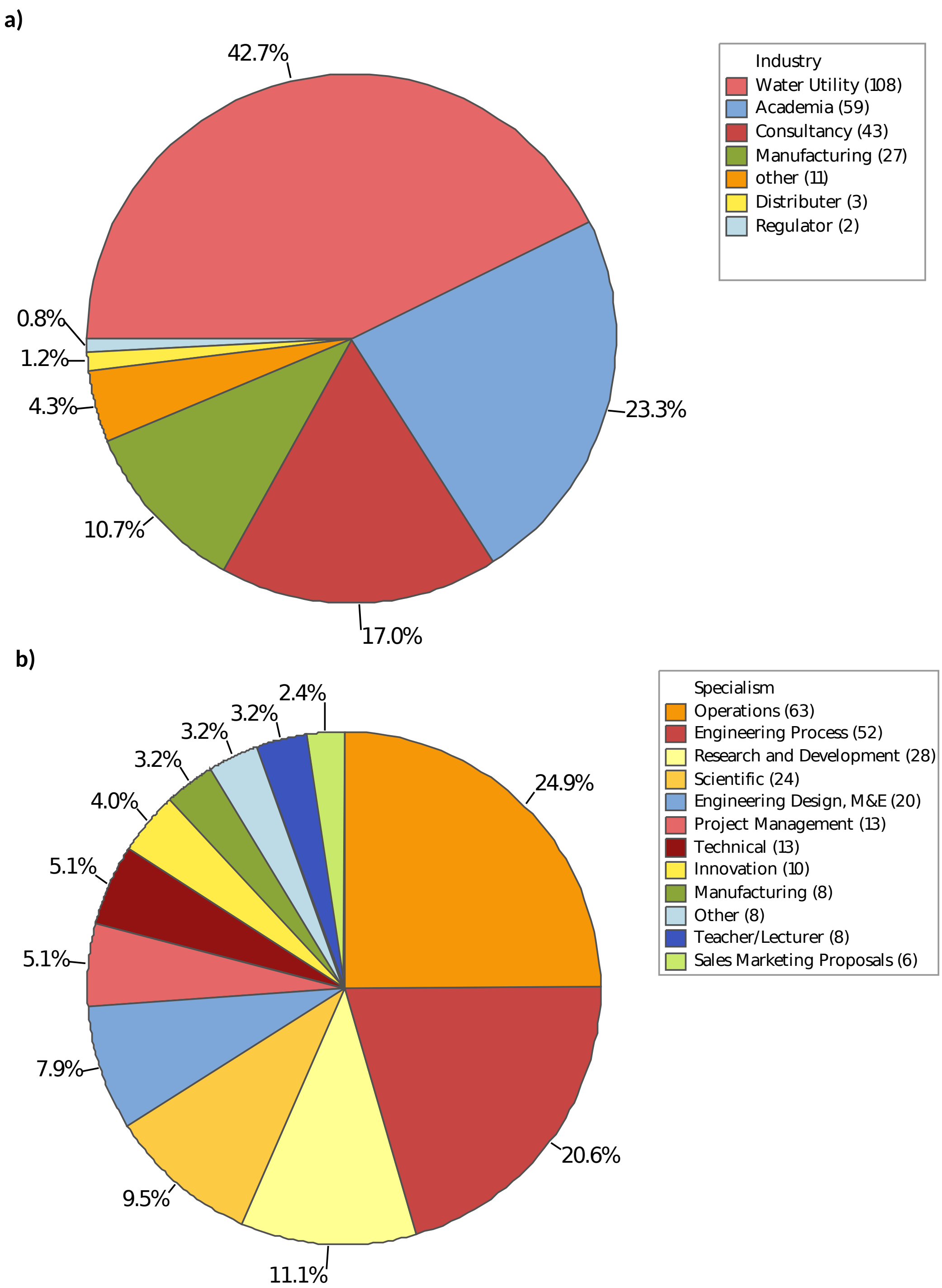

Fig. 5 *Pie chart, with a) showing respondents by industry and b) respondents by specialism. n is shown in the legend, to the right of the specialism.*

3.2. Decision-making tool use and decision importance by specialism

It is important to evaluate the decision-making tools used by industry and academic specialists, along with their decision-making strategies. With that in mind, respondents were asked to state the method they most commonly used out of, Written Notes, Spreadsheets, Simulation, Environmental Decision Support Systems (EDSS), Opinion, Mathematical Modelling or Nothing. The outcomes are shown in Fig. 6, with specialism on the x-axis and proportion of the sample population on the y (%). By far, the most commonly used method was the use of personal or company-specific Spreadsheets, with 33% (*n=83*). Spreadsheets are extensively used by those working in operations, Engineering Process, Scientific and Technical disciplines. All of which use numeracy to perform calculations and demonstrate new ideas or concepts. Understandably, teachers/lecturers working in the subject of wastewater engineering used spreadsheets the least, as they are less likely to use numerically conceptualise new ideas or concepts in a commercial context.

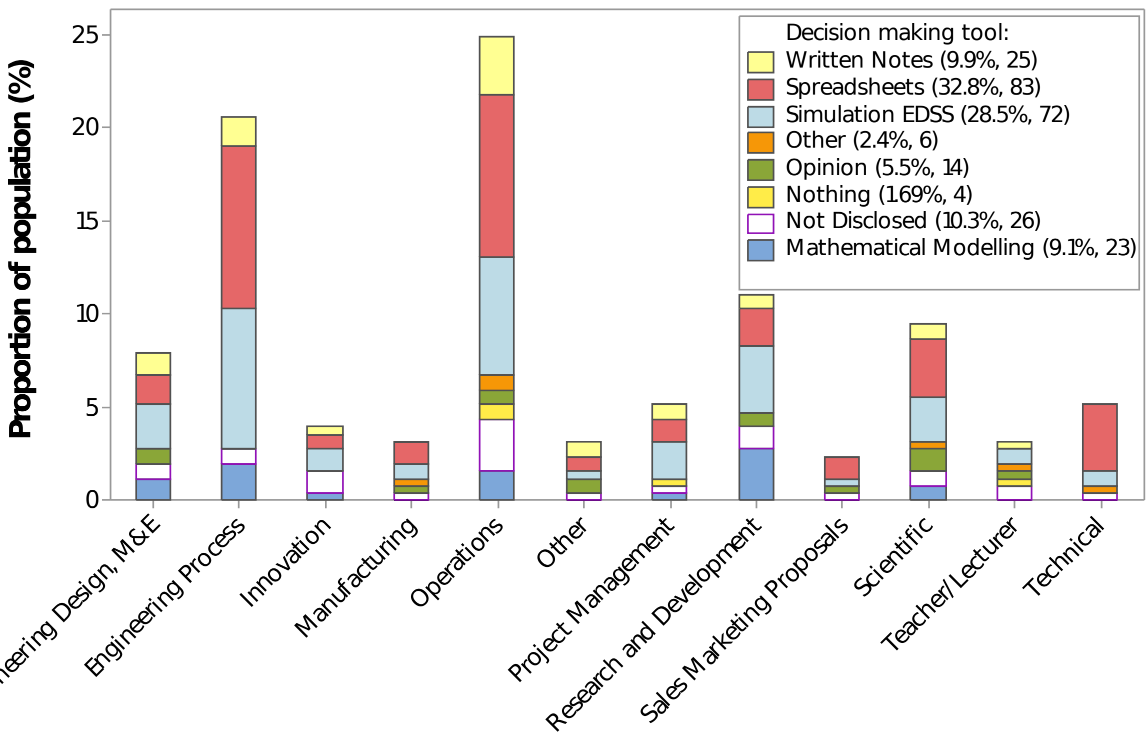

Fig. 6 *Stacked bar chart showing the decision-making tool by specialism. Where the x-axis is showing the area of specialism; the y-axis, percentage of the respondents, with stacks representing the proportion of the sample-set used by the particular specialism. To the right of the legend entry, shown in brackets is the overall percentage of respondents, followed by the overall number of respondents.*

The second most popular method shown in Fig. 6 was simulation and EDSS, with 29% (*n=72*) used by respondents to simulate wastewater treatment processes, while providing some form of EDSS. The fractionation of packages and respondent use is continued in the entries to Table 1. Engineering Process was the largest user of simulation and EDSS software packages, with 26% (*n=19)* of the users which has a direct relationship with their primary job function of delivering compliant wastewater treatment processes. Fig. 7 shows that those in Engineering Process who disclosed a reason for using simulation and EDSS used these tools to provide 'accuracy of information'. Other studies have found that EDSS and simulation have also been used to reduce the cognitive demand required, using models based on adaptations of the IWA benchmark simulation models (Copp, 2000; Dalmau et al., 2006; Lorenzo-Toja et al., 2016). Fig. 6 also demonstrates that EDSS and simulations are presently limited to numerically qualified engineers and those with the education and training to calibrate the underlying models, due to the large number of complex parameters (Bachis *et al*., 2015; Cosenza, Mannina, Vanrolleghem, & Neumann, 2013; Zeng, Soric, & Roche, 2013).

The third-largest method used was Written Notes, with 10% (*n=25*) of respondents favouring them as a method of decision support (Fig. 4). For an industry where non-compliance with treatment standards can have severe environmental impacts, this is somewhat concerning, due to the risk of loss and destruction of important wastewater process information. Furthermore, information stored in this way prevents data mining and in-depth statistical analysis (knowledge management). The most significant users of Written Notes were respondents in Operations with 13% (*n*=8), followed by Engineering Process and Engineering Design (M&E), with 8% (*n=4*) and 15% (*n=3*) respectively. Operations respondents were also least likely to disclose information, with 11% (*n*=7) choosing not to disclose the decision-making tool used (Fig. 6), and 33% (*n=21*) for the decision importance (Fig. 7). In an industrial context, operational staff are likely to value empirical knowledge rather than statistical numerical information, keeping written notes on observations. The importance of these observations has been noted by Hernández-Chover, (2019) when performing cost analysis on age-related, wastewater process deterioration.

Mathematical Modelling is used by 9% (*n=23*) of respondents, with Research and Development (R&D) the most significant users of Mathematical Modelling software tools, with 25% (*n=7*) of the grouped data (Fig. 6). This observation corresponds with the findings of Lee (2017), who found mathematically modelling technology opportunities for R&D project selection allowed exploitation of short lifecycle technologies. Therefore, R&D project selection favours the use of mathematical modelling packages, such as MATLAB®, Octave, and Python due to the multi-objective digital manipulations that can be achieved from large datasets. The second most significant users of Mathematical Modelling tools were Engineering Process, with 9% (*n=5*) of the grouped data and Operations with 6% (*n=4*). Both disciplines perform numerical manipulations for the justification of process engineering design concepts and operational changes, so it is common for accurate modelling tools to be used (Ebrahimi *et al*., 2017). This corresponds with Fig. 7, where Engineering Process and Operations value the 'Accuracy of information'. Evidence of this was also found in the overall number of respondents, where 35% of respondents (*n=89*) considered 'Accuracy of information' most important when making a decision (Langergraber, Pressl, Kretschmer, & Weissenbacher, 2018). This is followed by the 'Robustness of outcomes', with 11% (*n=28)* and 'Application of outcomes', with 9% (*n=23*). Cost implications of outcomes and the judgement of expert consultants were considered least valuable by respondents with 5% (*n=13*) and 4% (*n=11*) respectively. Out of all the groups Engineering Process had the highest appreciation for the 'Cost implications', which forms a large part of their role, where process optimisation can substantially reduce operational costs (Serdarevic & Dzubur, 2019). Conversely, Manufacturing, Innovation, Sales Marketing proposals and Technical showed no consideration for the 'Cost implications of the outcomes'. Furthermore, they are least likely to use the judgement of expert consultants to generate decisions.

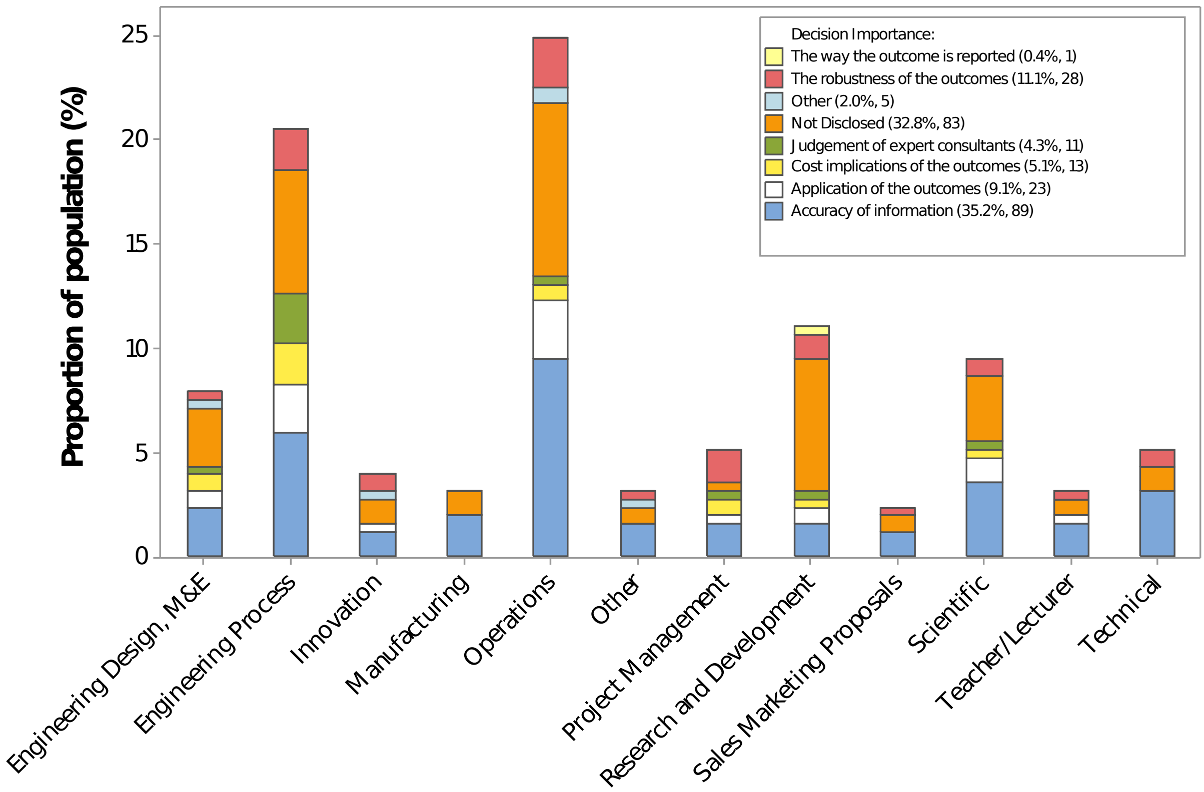

Fig. 7 *Stacked bar chart showing decision importance by specialism. Where the x-axis is showing the area of specialism; the y-axis, percentage of the original sample population, with stacks representing the proportion of the sample-set used by the particular specialism. To the right of the legend entry, shown in brackets is the overall percentage of respondents, followed by the total number of respondents.*

3.3. Summary of software application use

Software applications were used by a minority of respondents (29%, *n*=72), with only 9% (*n*=23) disclosing the type of software they used. Table 1 shows the software applications used by respondents, along with their specialism and software application use in h.week^{-1}. Ten software applications were used by respondents, covering Asset design/management, Simulation EDSS, Mathematical Modelling and Statistics. The most popular software applications were Spreadsheets, with 33% (*n=83*) of respondents, where Engineering Process and Operations were the most extensive users (Section 3.2). Hence, Engineering Process, and in particular Operations are thought to use spreadsheets because they are a convenient tool for capturing empirical, experience-based process data. Moreover, where operations have a greater appreciation of overall plant performance; they can effectively intuitively screen uncertainty in datasets using expert judgement. The second most popular software application, used by a wide range of technical specialisms, was BioWin, by EnviroSIM (EnviroSIM, 2018). The most significant users of BioWin were Engineering Process (*n=4*), using the application for a mean of 11.8 $h.week^{-1}$. From the qualitative data, the users of BioWin favoured time savings (*n*=*2*) and the reduction in the potential for errors (*n*=*2*). Users also stated they used the dynamic analysis and valued the wastewater process plant insights it gave. Moreover, they used BioWin to extend internal knowledge, such that process models can be applied widely within their organisation. This indicates that users of BioWin, particularly in the Engineering Process specialism use it to generate dynamic plant-wide simulations of existing wastewater treatment processes (Li, Nan, & Gao, 2016; Liwarska-Bizukojc & Biernacki, 2010; Nghiem et al., 2017).

Matlab/R was the third most used software application (35% (*n*=*8*)), with an even utilisation in Engineering Design M&E, Engineering Process, R&D and Operations (*n*=*2*). Therefore, as described in Section 3.2, Mathematical Modelling packages are being used by those performing conceptual modelling of wastewater treatment processes. Users spent a mean of 13.1 $h.week^{-1}$, which was the highest software application use; however, there was considerable variation in results, which is evident in the median value of 8.8 $h.week^{-1}$. When considering the qualitative data, the essential themes were that the majority (*n*=*3)* of

Mathematical Modelling software users preferred to use the software for the fair comparison of options and to reduce the time taken for mathematical simulations. This is also well documented in the literature with mathematical models in most following the IWA Benchmark simulation modelling methodology (IWA, 2018; Jeppsson et al., 2007; Vrecko, Gernaey, Rosen, & Jeppsson, 2006). Matlab/R are also well documented in the literature, particularly when optimising wastewater treatment processes using machine learning techniques and simulations (Bagheri *et al*., 2015; Moon, Kim, & Linninger, 2011). Therefore, it is anticipated that the number of wastewater professionals and academics using mathematical modelling will increase over time to test and validate methodologies for the predictive optimisation of wastewater treatment processes. However, before that can happen a better understanding of resilience and separation of the stressor from process stress as shown in Fig. 2.

Table 1. Respondent use of software applications, as primary and secondary applications. With n shown in round brackets to the right of the tabulated values. Median usage values are shown in square brackets beneath the mean.

Software application	Application	Specialism (n)	Primary utilisation (%)(n)	Secondary utilisation (%)(n)	Usage (h.week^{-1})
Aspentech	Asset design/management	Manufacturing (1.0)	4.34 (1.0)	0.00 (0.0)	[1]5.00 (1.0) [5.00]
BioWin (EnviroSim)	Simulation EDSS	Innovation (1.0) Research and Development (1.0) [4]Engineering Process (4.0) Scientific (1.0) Engineering Capacity (1.0)	21.73 (5.0)	13.04 (3.0)	11.78 (8.0) [11.25]
Excel	All applications	Engineering Design M&E (7.0) Engineering Process (23.0)	8.69 (2.0)	4.34 (1.0)	7.70 (5.0) [10.00]

		Innovation (1.0)			
		Operations (22.0)			
		Project Management (5.0)			
		Research and Development (8.0)			
		Sales Marketing Proposals (3.0)			
		Scientific (6.0)			
		Technical (7.0)			
GPS-X (Hydromantis)	Simulation EDSS	[1]Innovation (1.0) Research and Development (1.0) Scientific (1.0)	17.43 (4.0)	4.34 (1.0)	6.13 (2.0) [6.13]
Hach (WIMS™)	Asset management	Engineering Process (1.0)	8.69 (2)	0.00 (0.0)	-
MatLab/R	Mathematical modelling	Engineering Design M&E (2.0) Engineering Process (2.0) Operations (2.0) Research and Development (2.0)	8.69 (2)	26.08 (6.0)	13.07 (8.0) [8.75]
Minitab	Statistics	Operations (1.0) Teacher/Lecturer (1.0)	8.69 (2)	0.00 (0.0)	3.50 (2.0) [3.50]
Maximo	Asset management	Asset Maintenance (1.0)	4.34 (1)	0.00 (0.0)	2.00 (2.0) [2.00]
Simba	Simulation EDSS	[1]Engineering Process	4.34 (1)	0.00 (0)	8.00 (1.0) [8.00]
West (MIKE)	Simulation EDSS	[1]Teacher/Lecturer	8.69 (2)	0.00 (0)	4.25 (2.0) [4.25]

GPS-X by Hydromantis followed Matlab/R in the rankings (Hydromantis Environmental, 2018). Although fewer respondents used GPS-X, it was still used equally by Innovation, R&D and Scientific disciplines for a mean of 6.1 h.week^{-1}. This corresponds with the outcomes of BioWin in Table 1, which showed the same user groups. Minitab statistical analysis software was used for a mean of 3.5 h.week^{-1} to provide a “comparison of options” by respondents in both operations and academia (Minitab LLC, 2019). Although other software applications were used, the small number of respondents for each means they are not considered in the discussion.

As shown in Table 1, software applications are used to support the decision-making process for wastewater treatment process plants. However, only 42% (*n=30*) of the overall respondents used the outputs from analytical software applications to make decisions at an organisational level. The majority of respondents considered their method of decision making as accurate (89%, *n=152*). Of the remaining, 11% (*n=18*) that were not confident in their decision making strategy, the largest population were students (22%, *n=4*), followed by junior level employees (17%, *n=3*). The specialisms with least confidence in decisions were Engineering Process (22%, *n=4*)), followed by Scientific and R&D, with 17% (*n=3*). Possibly showing those with higher technical expertise had a greater appreciation for wastewater processes and perhaps recognised the complexity of decision making.

In this study, 29% (*n=72)* of respondents used software applications to support decisions with only 9% (*n=23*) stating the application they used. The limited use of EDSS (*n*=14) is a worrying prospect and means that numerous methods are being used, but with 33% of information stored in Spreadsheets; knowledge is held discretely and is not available for future reference (Abubakar, Elrehail, Alatailat, & Elçi, 2019). There has been much research undertaken in Simulation and EDSS, but full-scale testing has been rare (9% of publications) and relatively few commercial software tools have been developed (Corominas *et al*., 2018). However, 35% of those using EDSS software applications also perform mathematical modelling. Therefore, industry and academia are producing mathematical models to fit specific applications and achieve the required level of accuracy. Therefore, to increase the transfer of research methods into software applications, it is first critical to gain an appreciation for user requirements, to ensure take-up.

3.4 Process stress and benchmarking

In order to understand the concept of stress in wastewater treatment processes, it is first essential to gain an industrial and academic perspective of the term ‘stress’. So respondents were asked to state their understanding of process stress in wastewater treatment processes. The results showed commonalities in respondent answers, so responses were coded and grouped, as shown in Fig. 8, from PP to VB. Each code relates to a particular interpretation of process stress in wastewater treatment processes, which was provided by qualitative answers from the respondent population. Furthermore, to understand the influence of education level and work seniority, a ranking was applied between one and five. Each level of rank relates to seniority, from one the lowest to five the highest: 1) represents secondary school education; 2) A-Level, HND/C or associate degree; 3) BSc, BA or BEng; 4) MSc and 5) EngD or PhD. When considering role the rankings are; 1) represents student, trainee, junior level or employee general; 2) supervisory level; 3) manager, practitioner or section lead; 4) senior practitioner or senior manager and 5) head of department or director.

The results in Fig. 8 show the largest group in the respondent population, for both, ranked role and education, considered process stress a Variance from a Benchmarked condition (VB), with 51% (*n=45*) and 57% (*n=51*) respectively. The largest demographic within VB in Fig. **8**, were those educated at BSc, BA, BEng or Masters level (3-4) in a senior practitioner or senior manager role (4). Overall, the largest specialism in VB group was from Engineering Process with 32% (*n=45*) who are likely to work to mitigate the negative impact of variations from a benchmarked condition. From the qualitative data, respondents interpreted VB as a negative variation from the standard operating performance of a wastewater process or plant (benchmark). The second-largest group was Risk Reduction (RR), which relates to the reduction of effluent compliance failures by using an empirical or experience-based judgement on the level of process stress. The largest demographic in this group were those educated to Masters or EngD/PhD level in Head of Department/Director roles. Therefore, those that consider process stress as RR show a slight bias towards the more highly qualified in the most senior roles. Those with the least education (1–2) were also highly likely to consider process stress as a VB or were Un-Sure (US) of what the term meant. However, although the least educated have an appreciation of process stress as a VB; the qualitative data tells a slightly different story. It indicates that the least educated (1–2) are heavily reliant on a visual means of interpreting process stress and how it relates to adverse process conditions, such as process overloading or mechanical failures (Langergraber *et al.*, 2018). This observation corresponds with the response from Operations who are less sure of the term process stress, with 39% (*n=16*) Un-Sure (US) of the term.

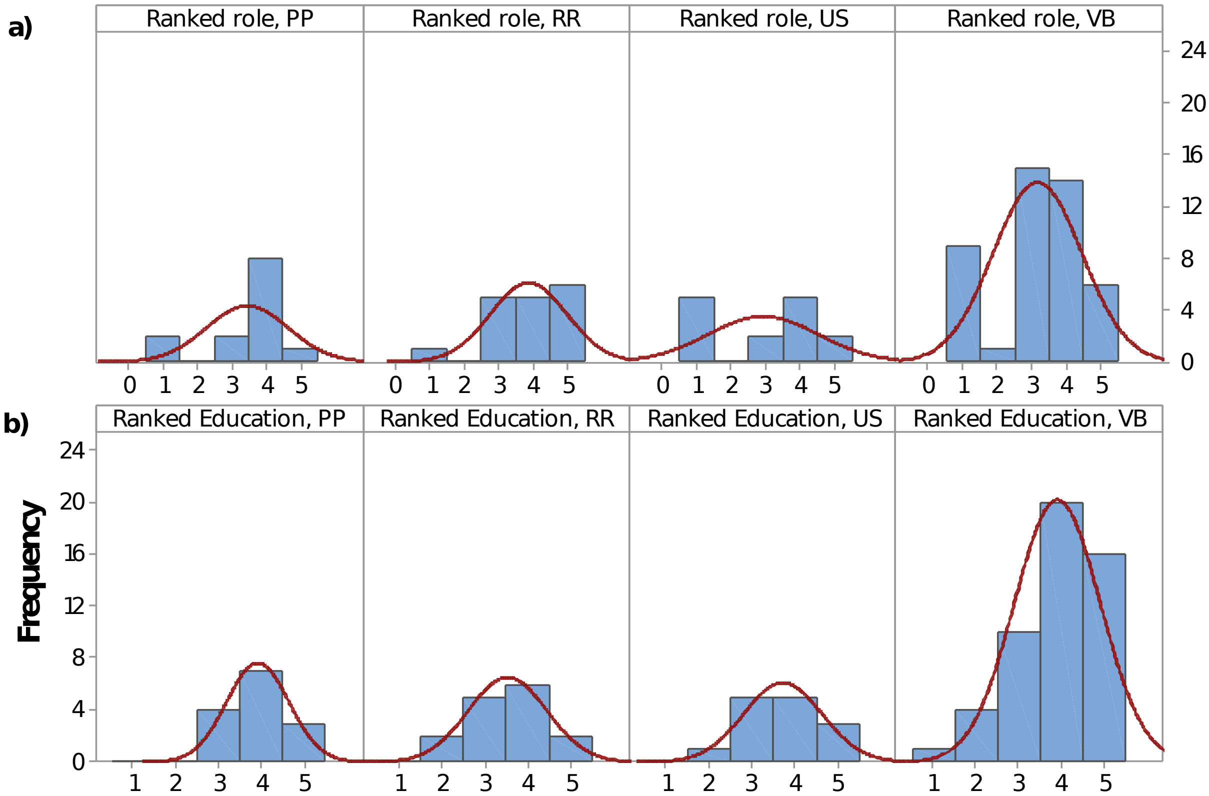

Fig. 8. Multiple coded frequency counts of variables histogram showing respondent understanding of process stress in wastewater treatment processes. Respondents are grouped by ranked role (a) and education (b), showing respondent understanding of process stress. With, ranked education and ranked role (1-5) on the x-axis and number of respondents (n) on the y-axis. Each pane groups the coded process stress (understanding) variables and the frequency distribution. Where process stress (understanding) codings are defined as; Process Performance (PP), Risk Reduction (RR), Un-Sure (US) and Variance from a Benchmark (VB).

Respondents were also asked to state what they considered most important about process stress in wastewater treatment processes. Again, respondent answers showed similarities in opinion, so responses were coded, as shown in Fig. 9, from DA to US. The rankings for the level of education and role (1–5) in Fig. 9 are the same as Fig. 8. The largest grouped respondent population in Fig. 9a and Fig. 9b were those that considered Stress Measurement (SM) most important in wastewater treatment processes, with 54% (*n=51*). The highest contribution of respondents that viewed SM as most important was those educated to Masters level (4) (*n=21)* in a Senior Practitioner or Senior Manager role (4) (*n=19*). This observation also correlates with VB in Fig. 8; however, it should be noted there is an overall bias in the respondent population toward those educated at Masters degree level, with 32% (*n=78*), acting as both, Head of Department/Director (5) and Senior Practitioner/Manager (4), with 26% (*n=61*). Therefore, those with a Masters degree and in a senior role have identified a definite requirement to measure process stress. When respondents were asked if an analytical tool for the measurement of process stress would be useful to them 82% (*n=96*) answered ‘yes’. Qualitative responses also correlated, with respondents identifying a requirement for a tool that considers and analyses process stress. However, there is a significant difference in opinion on how it should be applied to wastewater treatment processes. This observed difference in opinion is thought to relate to the broad range of specialisms, role and education level of respondents in this study and, range of departmental and specialist decision bias.

The second-largest respondent population in Fig. 9 was Process Efficiency (PE) and Resource Measurement (RM), with 16% (*n=15*) and 17% (*n=13*) respectively. From the qualitative data, respondents that valued PE found the direct measurement and analysis of process stress in wastewater treatment processes as important. Whereas, respondents that valued RM were interested in the quantification of resources associated with the operation and maintenance wastewater treatment processes. These resources include operational resource (labour), operational maintenance (O&M), safety protection equipment and less tangible resources such as knowledge and experience. This human resource (operational labour) observation is not well covered in the literature, with the IWA, (2018) operational cost Index (OCI) only accounting for the direct costs associated with the wastewater treatment process operation. Although accounting for power, chemicals and returns from CH_4 generated in anaerobic digestion it excludes operational resource which can be a significant contributor to operational costs. To summarise the similar numbers of respondents for RM and PP correlate with VB shown in Fig. 8, where physical resources can have a direct impact on process efficiency and in-turn increase the negative variation from a benchmarked operating condition. Moreover, the consensus of those in industry and academia is that process stress is the negative magnitude of stressor influence on a wastewater process from a benchmarked condition.

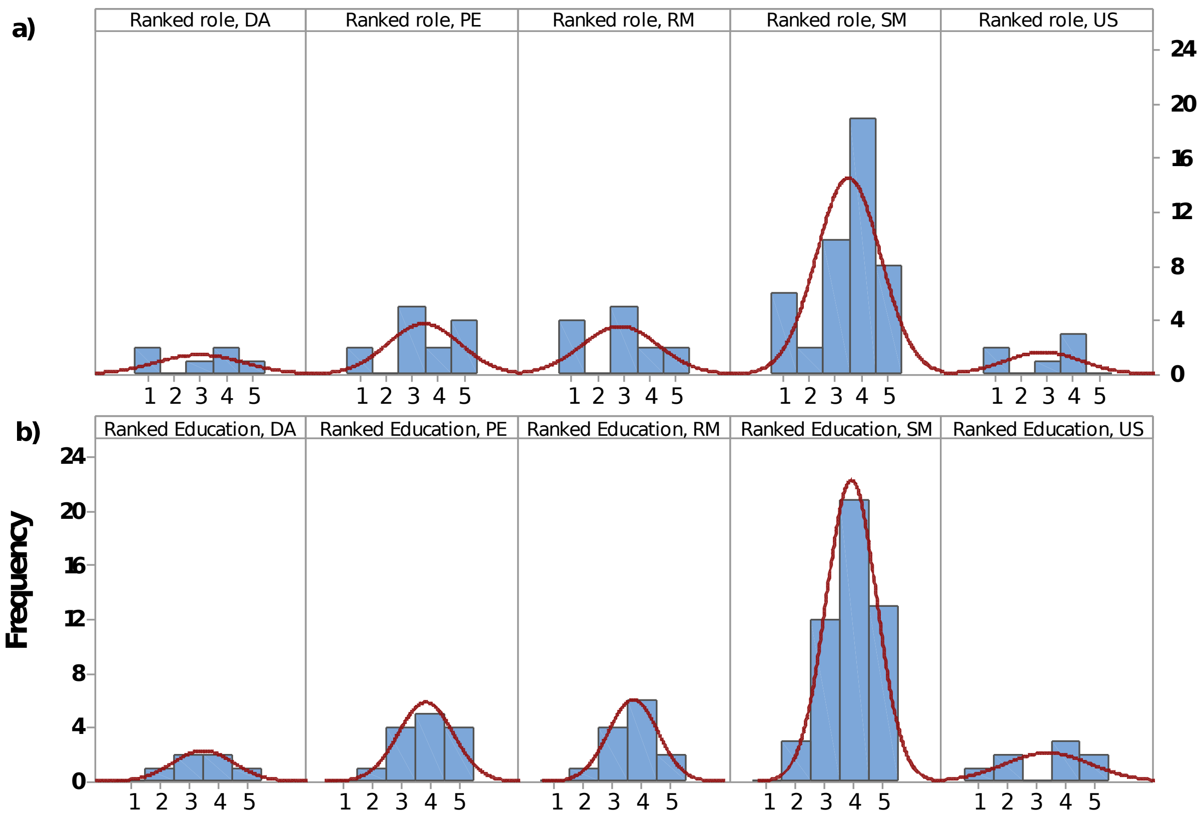

Fig. 9 *Multiple coded frequency counts of variables histogram showing respondent understanding of the importance of process stress in wastewater treatment processes. Respondents are grouped by ranked role (a) and eduction (b), showing respondent understanding of process stress importance. With ranked education and ranked role (1-5) on the x-axis and number of respondents on the y-axis. Each pane groups coded process stress (importance) variables and the frequency distribution. Where process stress (importance) codings are defined as; Data Accuracy (DA), Process Efficiency (PE), Resource Measurement (RM), Stress Measurement (SM) and Un-Sure (US).*

As a fundamental part of resilience theory, benchmarking is used to measure changes in operating conditions from a standard base measurement (Sweetapple *et al.*, 2019). To evaluate the academic and industrial understanding of the term benchmark, respondents were asked how benchmarking relates to their present role. Again, commonalities were found in respondent descriptions, so they were coded from CP to TP, as shown in Fig. 10. The same rankings, used in Fig. 8, were used for education and role level (1–5), with one the lowest and five the highest. This again, allowed segregation of opinion based on education level and role to and the grouped understanding of the term benchmark.

The largest grouping in Fig. 10 was Starting Point (SP), with 39% (*n=42*). Therefore, the majority of respondents understood the term 'benchmark' as a SP, from which changes can be made and scenarios simulated. This observation was also confirmed by the largest respondent specialism within the group, which was Engineering Process (*n=15*) who are directly responsible for engineering and making informed process changes. The education ranking remained the same as Fig. 9, where those educated to Masters level (4) in a Senior Practitioner/Senior Manager role were most likely to understand the concept of a benchmark as a SP. Thus, variations from a SP are recognised as a variance from standard operation conditions, which Juan-García *et al.*, (2017) defined as the influence of a stressor. Therefore, when the stressor (cause) is separated from process stress (effect) in wastewater treatment processes, the magnitude of the reaction produced by a stressor gives insight into the instantaneous measure of process stress (Butler *et al.*, 2016).

The second-largest respondent population was Comparison Point (CP), where respondents understood 'benchmark' as a point from which comparisons can be made, with 27% (*n=29*). Roles were more evenly distributed for CP as shown in Fig. 10a, but the overall bias is toward those on a Senior Practitioner/Manager role, whereas ranked education level shows a more gaussian trend with both those with BSc, BA or BEng and Masters degrees showing the highest proportions. Those respondents understanding benchmark as an OP were most likely to have a Masters degree (4) and work in a supervisory capacity.

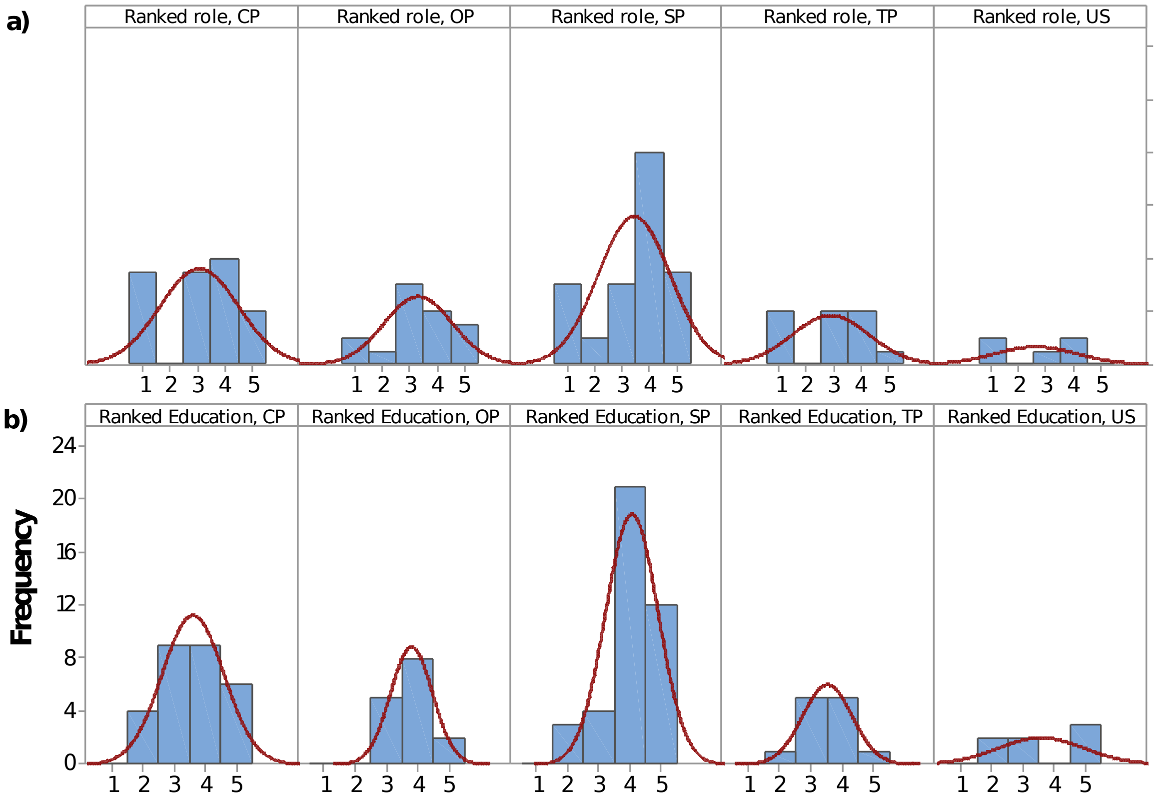

Fig. 10 *Multiple coded frequency counts of variables histogram, grouped by ranked role (a) and education (b), showing respondent understanding of the term 'benchmark'. With ranked education and ranked role (1-5) on the x-axis and number of respondents on the y-axis. Each pane groups coded 'benchmark' variables and the frequency distribution. Where benchmark codings are defined as; Comparison Point (CP), Optimal Point (OP), Starting Point (SP) and Target Point (TP) and Un-Sure (US).*

To summarise, the concept of process stress was well understood as the negative variance from a benchmarked condition. Overall, the consensus from the respondents was that process stress in wastewater treatment is a potentially useful performance measure. Those with Masters Degrees/PhDs (4-5), with senior and directorial roles (4-5) having the best appreciation of process stress in wastewater treatment processes. This bias is thought to be related to the high level of education, which gives them a better theoretical basis for understanding process stress in wastewater treatment processes. An extremely significant observation was that 82% (n=96) of respondents considered an analytical tool for the measurement of stresses in wastewater treatment as important.

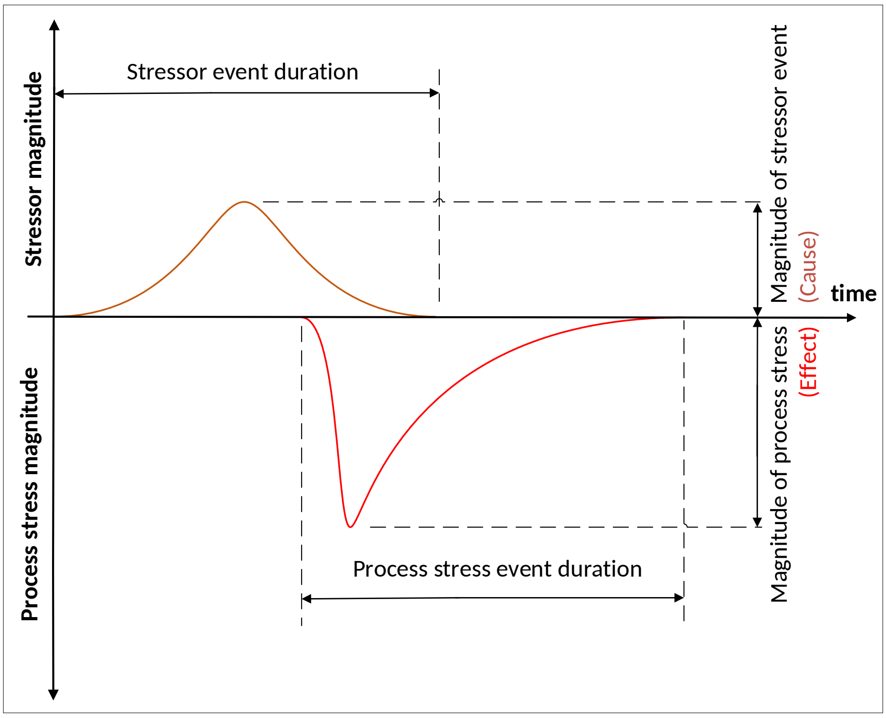

Fig. 11 *Decoupling the stressor from process stress.*

The results show that the understanding of benchmark varies dependent on how it is used, but in this study, with the majority considering it a starting point. Therefore, benchmarking sets a point, from which, adjustments are made to simulate process and operational changes. This analogy fits the description provided by Jeppsson *et al.*, (2007) of ‘objectively evaluating the performance of control strategies by simulating them using a standard model implementation’. Combining the understanding of benchmarking stated here and the concept of process stress isolates the requirement to analyse stresses in wastewater treatment processes. Hence, analysing the stressor independent of the process stress as shown in Fig. 11 will improve the understanding of resilience while allowing the exploitation of more sophisticated analytical methods such as machine learning.

4. Conclusions

This research article confirms the requirement to measure and analyse process stress in wastewater treatment processes, with 82% of respondents stating that an analytical tool would be useful to them. Respondents were able to conceptualise process stress in wastewater treatment processes, viewing it as the negative variance from a benchmarked condition. Furthermore, participants also had a good appreciation of benchmarking and their responses correlated well with IWA benchmark simulation modelling.

This research has identified that resilience and term 'stressor' encompasses two parts; first the stressor (cause) second the process stress (effect), both acting dynamically. Therefore, when isolating process stress, a positive and negative variation from a benchmarked condition demonstrates the magnitude of a stressor and, in-turn process stress in an existing wastewater process. However, respondent understanding of process stress was limited to under capacity (negative variance), whereas overcapacity was not covered but presents unique challenges. A worrying observation in this was that 33% of respondents still used personal or company-specific Spreadsheets and 10% used Written Notes. Therefore, there is a significant variation in how information (Knowledge) is stored and managed, where information in spreadsheets and written notes has the potential for data loss or manipulation.

This research has highlighted the need for further research in the development of a robust method for the measurement and evaluation of stresses in wastewater treatment processes. Process stress measurement is likely to have far-reaching benefits with applications to, physical, biological and chemical processes, both inside and outside the wastewater industry. More importantly, it will play a crucial role in the management of environmentally generated stresses in existing wastewater treatment processes due to climate change. In addition, industrial and academic consultation is required support observations noted by other researchers, in particular the uptake of analytical software tools, where only 29% of respondents in this survey used them.

Overall, both industry and academia require analytical methods, which measure stresses in existing wastewater treatment processes. Moreover, future methods should be used to supplement resilience to allow researchers to exploit machine learning and knowledge generation for the optimisation of wastewater treatment processes.

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