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A Neural Network Model for Decision-Making with Application in Sewage Sludge Management

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Abstract: Wastewater treatment (WWT) is a foremost challenge for maintaining the health of ecosystems and human beings; the waste products of the water-treatment process can be a problem or an opportunity. The sewage sludge (SS) produced during sewage treatment can be considered a waste to be disposed of in a landfill or as a source for obtaining raw material to be used as a fertilizer, building material, or alternative fuel source suitable for co-incineration in a high-temperature furnace. To this concern, this study's purpose consisted of developing a decision model, supported by an Artificial Neural Network (ANN model), allowing us to identify the most effective sludge management strategy in economic terms. Consistent with the aim of the work, the suitable SS treatment was identified, selecting for each phase of the SS treatment, an alternative available on the market ensuring energy and/or matter recovery, in line with the circular water value chain. Results show that the ANN model identifies the suitable SS treatments on multiple factors, thus supporting the decision-making and identifying the solution as per user requirements.

Keywords: waste-treatment process; sewage-sludge management; circular economy; decision support system; decision problem; artificial neural network

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1. Introduction

Climate change is a global crisis that has forced a more sustainable development of resources planning, analyses, and policymaking regarding the valorization of the limited resources on earth. The sustainability of industrial activities has now become crucial for many firms [1]. To this concern, increased awareness concerning greenhouse gas (GHG) emissions evaluation, mainly carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), was observed in recent years. In this context, the wastewater (WW) sector plays a crucial role in identifying needs, barriers, and new strategies to face the future's expected challenges [2]. According to Chai et al., the emissions due to the WWT are the sixth largest contributors to methane (CH_4) emissions and the third largest sources of nitrous oxide (N_2O) emissions, respectively [3]. Meanwhile, the management of the SS generated from WWT is one of the most controversial issues of modern cities. If, on the one hand, the new advanced WWT available on the market and the forced implementation of the European Directive 91/271/EC ensure a higher quality of the effluent treated, then, on the other hand, the amount of the SS produced in the process is significantly increasing. Recent studies showed that, in the last fifteen years, the EU-12 annual production of the SS increased by almost 50%, from 9.8 million tons in 2005 to over 13 million tons in 2020. The lack of continuity among official reports and the relevant lack of data for the new Member States further complicate the study of this topic [4].

The "Green Impact" was introduced to indicate all activities aiming at measuring and minimizing the negative effects on the environment [5]; traditionally, SS has been disposed of in landfills without prior treatment. The consequent impact on the environment of this waste and the uncontrolled generation of pollution dangerous to human health led the authorities to adopt a sustainable growth policy. To address these problems, the European Union has set the target to reduce the final waste disposal by 35% in 2016 (compared to 2000) in all Member States (EU Directive 99/31). Therefore, in recent years, the interest and request for new and more efficient SS management methods have exponentially increased.

According to Smol et al., the traditional water value chain should be rethought, rethinking how to use resources to create a sustainable economy, which is "free" of waste and emissions [6]. In other words, the authors consider as not sustainable a linear approach on the WWT, where the SS is considered waste. The authors, on the contrary, promote a "circular approach" (Figure 1), where the SSs produced are resources for agriculture, pharmaceutical and personal care products, renewable energy production, and co-firing as construction materials.

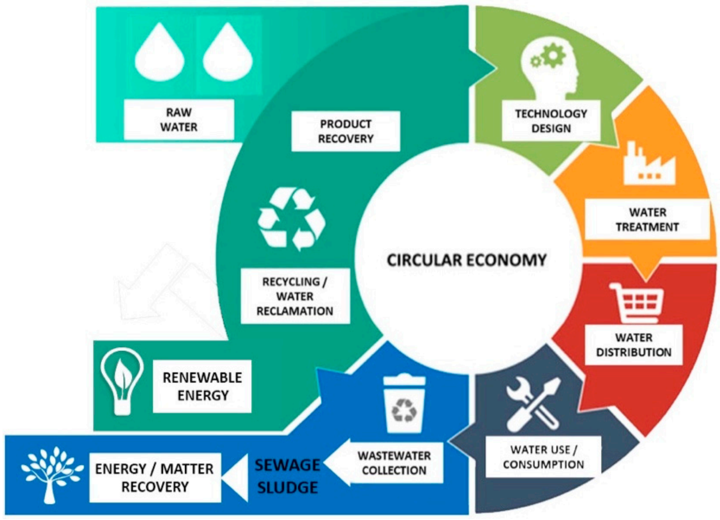

Figure 1. Circular water value chain (adapted from Zvimba's Circular Economy model for water and wastewater management).

In this scenario, promoting sustainability as operational strategy is considered a win-win strategy [7]. Therefore, the choice regarding the SS treatments, made in the context of a wastewater treatment plant (WWTP), has a significant impact. On the one hand, this choice must be consistent with the objective of environmental sustainability and rethinking of the wastewater value chain in a circular perspective, and, on the other hand, it must be economically sustainable. It is estimated, indeed, that the costs associated with the processing and the management of SS constitute 50% of the annual operating costs of a WWTP [8]. Making a choice that is consistent with these two aspects, however, is highly complex. According to Bertanza et al., indeed, SS decision problems can be defined as "wicked" problems, i.e., problems involving multidisciplinary aspects, such as economic, social, technical, and regulatory aspects, and a large number of stakeholders with often conflicting interests, interacting with each other in a fragmented network that is not clearly defined. As a result of this high degree of complexity and lack of clarity, the decision-makers tend to simplify the problem and take wrong decisions which optimize none or only some of the aspects to consider. Consequently, it is necessary to support the decision-makers with the target to facilitate the decision-making process concerning the SS treatments, thus allowing for a multi-objective optimization of the processes.

Consistent with the observations mentioned above, to fully investigate the research problem, the following subsidiary research questions are raised:

- Which SS treatments are available on the market and which combination of these can be considered more efficient in economic terms and consistent with a circular water value chain?
- What are the key drivers that affect the SS treatment efficiency?

- Does any tool exist to support decisions regarding SS treatment and to guarantee an effective management of SS?

Hence, the purpose of the study consisted of developing a decision model, supported by an Artificial Neural Network (ANN model), allowing us to identify the most effective sludge management strategy in economic terms. Consistent with the aim of the work, the suitable SS treatment was identified, selecting for each phase of the SS treatment an alternative available on the market, ensuring energy and/or matter recovery in line with the circular water value chain.

The rest of the paper is organized into the following sections: Section 2 details a literature review on SS treatments and on the development of decision models for the SS management. Section 3 describes the materials and methods adopted for the ANN model development. The results and the discussions are given in Section 4. Implications to practitioners, limitations, and future research directions are provided in Conclusions.

2. Literature Review

A systematic literature network analysis (SLNA) was adopted to identify the papers to be investigated. All the search terms and their combinations were searched for in the title, abstract, and keywords on Scopus, the largest scientific peer-reviewed literature database. References [9,10] introduce the keywords used in the literature review. They are split into three subsets:

- Subset 1: keywords related to SS treatment and its principal sub-processes (e.g., SS, SS management, WWT, WW, etc.).
- Subset 2: keywords related to sustainability (e.g., circular economy, green, environment, greenhouse gas, etc.).
- Subset 3: keywords related to decision support systems (DSSs) in SS management (e.g., decision theory, decision making, decision support techniques, etc.).

The keywords of Subset 1 and Subset 2 were combined with Subset 3 in the title, abstract, or keywords.

No public year limitation was used, and all articles published in English were selected from peer-reviewed journals indexed by Scopus; 24 papers were identified. Nine manuscripts were collected, refining the research to consider only papers published from 2014.

The authors' keywords analysis of the collected papers allowed us to detect through the co-occurrence network map (Figure 2) the scientific literature pattern covered by available scientific studies. The keywords co-occurrence network map evaluation showed that three clusters in published scientific studies could be identified. The first one is related to SS treatments; the second one is focused on sustainability in WWT, as well as in SS treatments; and the third one investigates the application of DSS to SSs management.

In the first cluster, Reference [11] introduced a new drying technology to reduce the pollutants due to heavy metals in SS, allowing for the adoption of the same SS on the agricultural lands as organic fertilizer rather than incineration or landfilling. An innovative centralized SS management of the co-composting process with the purpose to reduce the current economic and technological disadvantages of the individual treatment was presented by Reference [12]; the authors proved the efficiency of the management solution in terms of economically attractive physical–chemical characterization of SS treated, as well as odor emissions.

The second cluster identified by the co-occurrence network map is related to sustainability in WWT that SS treatment. An optimization problem solved by using a multi-objective mixed-integer linear program that includes three possible options, namely co-incineration, co-processing, and mono-incineration, was developed for the treatment of the digested SS produced in the Canton of Zürich. The model combining material flow analysis, process models, life cycle assessment (LCA), and mathematical optimization techniques allowed for the improvement of the environmental impact of the selected treatment. The sensitivity analysis results showed a reduction of environmental impact categories considered in the range of 2–6%, with a reduction of the energy consumption of 42% [9]. Life Cycle Assessment (LCA) is a widely used method for evaluating different treatment alternatives, but it is focused on an environmental assessment, without considering other aspects (e.g., economic, technological, etc.). To this concern, Buonocore et al. developed an LCA to compare the environmental performance of different alternatives for the disposal of the WWT and the SS in a WWTP in Southern Italy. They considered different scenarios with a progressively circular pattern, starting from the as-is scenario of the WWTP considered, and observed, as expected, that the greater the circularity of the strategy adopted, the lower the impact in different categories, such as the Global Warming Potential, Freshwater Eutrophication Potential, and Human Toxicity Potential [13]. In Reference [14], the LCA methodology was applied to identify the most environmentally sustainable way to dispose of SS between fluidized bed incineration and a cement kiln employing SS as a secondary fuel. Similarly, Wielgosinki et al. developed an LCA to evaluate the environmental performance of SS incineration and to provide information for improving the operating conditions of the treatment from an environmental sustainability perspective [15]. Gourdet et al. applied the LCA methodology to evaluate the environmental impact of the technological parameters related to the SS treatments, considering the thickening treatment, the anaerobic digestion with the cogeneration of heat and electricity, the mechanical dewatering, and the spreading of the SS on agricultural land. They found that the environmental performance of SS treatment could be improved by increasing biogas production by reducing $FeCl_3$ consumption for prior treatment to dewatering and by identifying alternatives for handling SS return liquors [16].

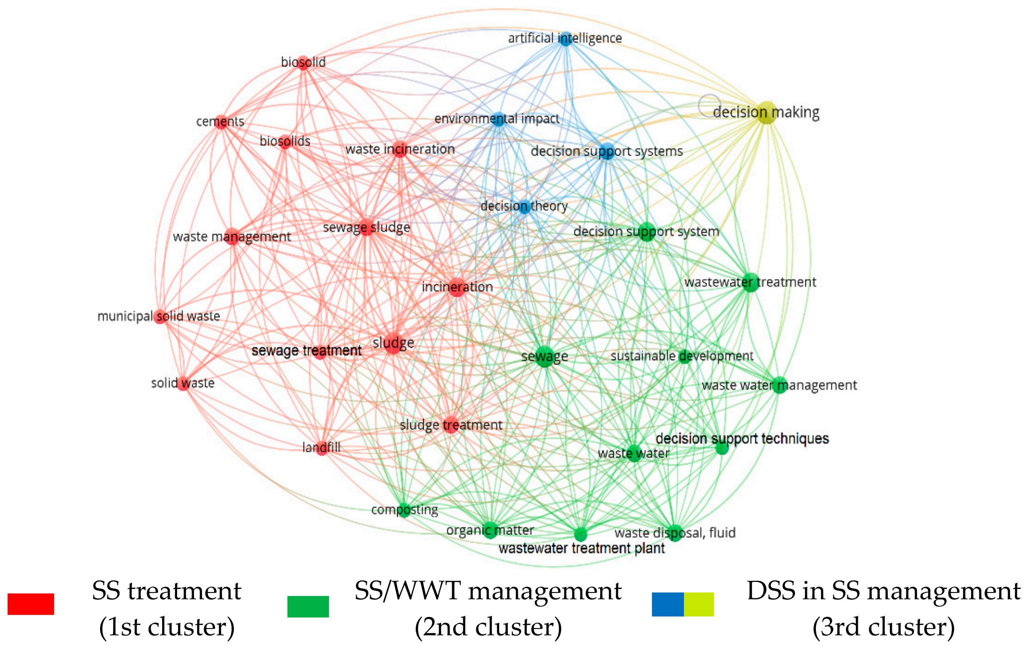

Figure 2. Authors' keywords co-occurrence network map.

Concerning DSS in SSs management (i.e., third cluster), recently a process data analytics platform for adopting the soft sensors in waste-to-energy (WTE) plant was developed. The platform uses machine learning methods coupled with big-data processing tools and cloud computing technologies. The platform's application allowed them to monitor the process parameters to maximize the performance of the WTE plant [17]. A similar approach was adopted for the management of the healthcare waste disposal system. In this context, a decision-making trial and an evaluation laboratory (DEMATEL) method were developed to digitally connected healthcare centers, waste disposal firms, and pollution control board. In this way, efficient monitoring of the entire waste supply chain improves the performance under the environmental perspective [18]. A comprehensive decision model, including technical, environmental, economic, and social factors for the evaluation of SS treatment strategies, was proposed by Reference [19]. The model was tested on a case study of 500,000 inhabitants; the authors proved the model's significant added value if it is properly employed. Consistent with this aspect, the main limitations of the decision model introduced were related to the user's strong dependency. In other words, the user plays a fundamental role in phases such as the data-collection process and result interpretation; therefore, inexperienced users could yield meaningless outcomes even if using the tool in a formally correct way. An et al. applied a Logarithmic Fuzzy Preference Programming based Fuzzy Analytic Hierarchy Process (LFPPFAHP) and Extension theory to assess the sustainability of three ways of SS management (i.e., composting, incineration, and resource utilization). As a result, composting was defined as "Moderately Sustainable", incineration as "Not Sustainable", and resource utilization as "highly sustainable" [20]. The adoption of SS for energy production was faced in 2018, by Naqvi et al., in the study conducted; an ANN model was employed to predict the thermal decomposition of high-ash sewage sludge. The results achieved showed a good agreement between the experimental values and predicted values [21]. The same method was adopted to predict the daily sewage sludge quantity in WWTP; in this case, different ANN architecture was evaluated to increase the prediction reliability. The minimum value of the root mean square error (RMSE) and mean absolute error (MAE) was identified by adopting the six mother wavelet (W) functions as preprocessor [22]. An ANN trained with back-propagation (BP) algorithm and a generalized regression neural network model (GRNN) were compared to predict the thin-layer drying behavior in municipal sewage sludge during hot-air forced convection. The research proved a better performance of the BP model to predict the moisture content of the sludge thin layer than the GRNN model [23].

The papers considered can be classified according to dimension evaluated (i.e., technological and economic), features of the method adopted, and possible application of multiple-criteria decision-making (MCDM). A summary of the researches identified is provided below (Table 1).

Table 1. Summary of the scientific research identified, classified according to dimension evaluated, features of the method adopted, and possible application of multiple-criteria decision-making.

Reference	Dimension				MCDM	Method Features
	Tec.	Ec.	Env.	Soc.		
Vadenbo et al. [9]	×	×	√	×	×	multi-objective mixed-integer linear program
Harder et al. [24]	×	×	√	×	×	LCA-QMRA
Bertanza, Baroni and Canato [19]	√	√	√	√	√	Home-made solution D-sight (PROMETHEE and GAIA)
An et al. [20]	√	√	√	√	√	LFPPFAHP and Ex-tension theory
Buonocore et al. [13]	×	×	√	×	×	LCA
Gourdet et al. [16]	×	×	√	×	×	LCA
Abuşoğlu et al. [14]	×	×	√	×	×	LCA
Turunen, Sorvari and Mikola [10]	√	√	√	√	√	MAVT
Wielgosiński et al. [15]	×	×	√	×	×	LCA
Durdević, Trstenjak and Hulenić [25]	√	√	√	√	√	AHP
Naqvi et al. [21]	√	√	√	×	×	ANN
Zeinolabedini and Najafzadeh [22]	√	√	×	×	×	ANN
Huang and Chen [23]	×	√	√	×	×	BP-ANN GRNN

Table 1. *Cont.*

Reference	Dimension				MCDM	Method Features
	Tec.	Ec.	Env.	Soc.		
Laura et al. [26]	√	√	√	√	√	Multi-attribute analysis
Kacprzak et al. [8]	√	√	√	√	√	Multi-attribute analysis
Ren et al. [27]	√	√	√	√	√	DEMATEL

Note: technological (Tec.), economic (Ec.), environmental (Env.), and social (Soc.).

3. Materials and Methods

The SS treatment is mainly carried out to reduce the sludge weight and volume, and to stabilize its biological part, leading to reduced disposal cost, environmental impact, and risk of human health problems. The main phases of a SS treatment system (SSTS) can be summarized in six steps (Figure 3).

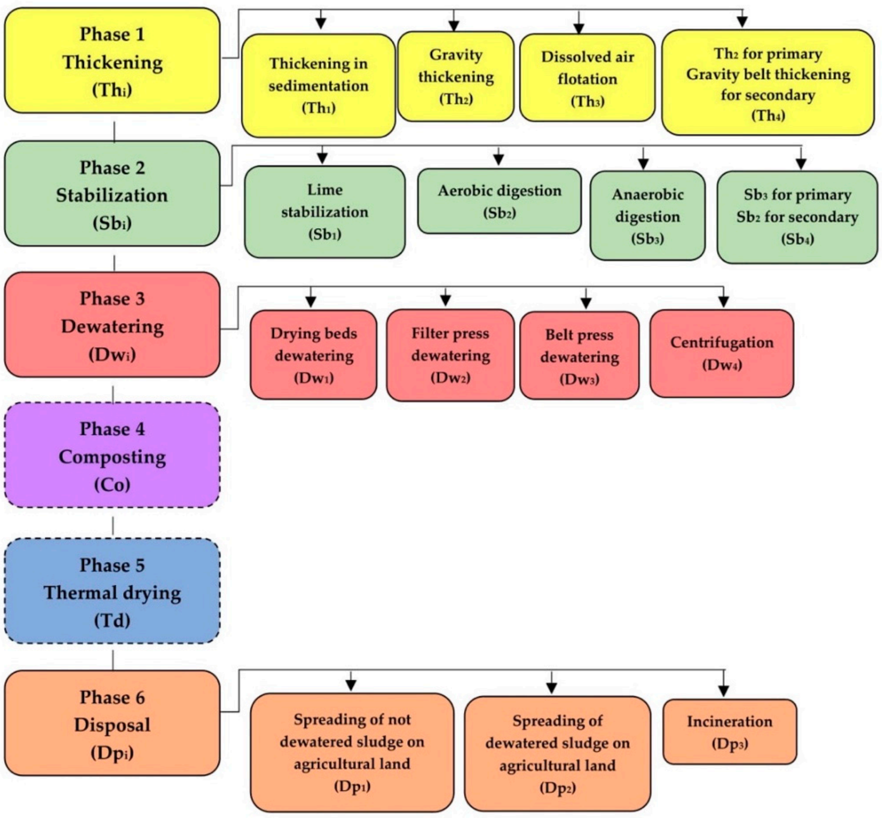

Figure 3. Summary of the unit operations for each phase of the SSTS. The ANN model neglects the alternatives available to carry out the phases included in the boxes with the dashed line.

Many strengths and limitations are included for each alternative; the literature review provides an interesting indication of the range of values possibly associated with each unit process. In this section, only a synthetic overview of each alternative's benefits and limits is shown. If, on the one hand, multiple elements can lead the decision-maker to a particular solution, then, on the other hand, the studies provide for different cases a clear indication of the most effective sludge management strategy under the economic and environmental perspective. The strengths and the limitations of alternatives considered are independent of specific conditions related to the place where the plants are located. The research conducted mainly focuses on the decision recommended by studies rather than on the specific aspects that affected the decision-maker's choice.

The first one is thickening (Th_i), which consists of increasing the solids concentration of the SS. The most commonly used thickening processes include sedimentation (Th_1) or gravity thickening (Th_2) or dissolved air flotation (Th_3) or hybrid, i.e., Th_2 and gravity belt thickening (Th_4) for primary and secondary sludge, respectively. The strengths and limitations of each alternative are shown in Table 2.

Table 2. Strengths and limitations of all considered alternatives to carry out the thickening treatments of the modeled SSTS.

Phase	Treatment	Strengths	Limitations
Phase 1 Thickening (Th_i)	Thickening in sedimentation (Th_1)	Low investment costs.	Water treatment interruption due to sludge removal.
	Gravity thickening (Th_2)	Moderate investment and management costs. Simple management of the process. Storage capacity.	Long detention times. It captures only sedimentable solids.
	Dissolved air flotation (Th_3)	Reduced detention times. Good reduction of suspended substances.	Considerable investment and management costs.
	Gravity thickening for primary sludge and gravity belt thickening for secondary sludge (Th_4)	The best treatment for both primary and secondary sludge. Good solids content in the sludge. Storage capacity.	Hard management.

Once the sludge is thickened, four options are identified for the stabilization, allowing us to reduce pathogens, eliminate odor, reduce organic matters, and prevent or inhibit future decomposition. The possible operations considered by the proposed model are lime stabilization (Sb_1), aerobic digestion (Sb_2), anaerobic digestion (Sb_3), or hybrid (i.e., Sb_3 for primary and Sb_2 secondary sludge), Sb_4. Below are summarized the strengths and limitations of each described alternative (Table 3)

Table 3. Strengths and limitations of all considered alternatives to carry out the stabilization treatments of the modeled SSTS.

Phase	Treatment	Strengths	Limitations
Phase 2 Stabilization (Sb_i)	Lime stabilization (Sb_1)	Simple management. Low sensitivity to toxic discharges. Good removal of heavy metals.	High operating costs due to the use of chemical reagents. Production of high volumes of sludge.
	Aerobic digestion (Sb_2)	Low investment and management costs. Low sensitivity to external factors. Low sensitivity to toxic discharges. No production of bad odors.	Intake of oxygen from the external environment is required. Sensitivity to climatic changes.
	Anaerobic digestion (Sb_3)	Intake of oxygen from the external environment is not required. Low energy consumption. Low production of stabilized sludge. High reduction of the pathogens in the sludge. Energy recovery.	Very high investment and management costs. Hard process management.
	Anaerobic digestion for primary sludge and aerobic digestion for secondary sludge (Sb_4)	Lower energy costs. Only primary sludge is subjected to anaerobic digestion.	Complex management of the processes.

The third step of the SS treatment consists of sludge dewatering through facilities such as drying beds (Dw_1), filter press (Dw_2), or belt press (Dw_3), or through centrifugation (Dw_4). The proposed ANN model does not consider the existing technologies related to compositing (Co) and thermal drying (Td) (i.e., Phases 4 and 5) of the SS treatment. The strengths and limitations of each alternative considered for dewatering, compositing, and thermal drying are summarized in Tables 4 and 5, respectively.

Table 4. Strengths and limitations of all considered alternatives to carry out the dewatering treatments of the modeled SSTS.

Phase	Treatment	Strengths	Limitations
Phase 3 Dewatering (Dw_i)	Drying beds dewatering (Dw_1)	Low investment costs. Low employment of highly specialized workers. Low energy and chemical reagents consumption. Low sensitivity to sludge characteristics.	High usage of area of land. The sludge must be previously stabilized. Climatic factors must be considered for the sizing of the system.
	Belt press dewatering (Dw_2)	Low energy consumption. Low investment and management costs. Simplicity of construction and maintenance. Good dry content of the treated sludge.	Production of bad odors. High sensitivity to sludge characteristics. Automatic management is not recommended. Dimensional reduction of the influent sludge.
	Filter press dewatering (Dw_3)	High dry content of the treated sludge. Moderate solid concentration in the filtered.	Discontinuous functioning. High investment and management costs. Special support structures are required. High usage of space. Highly specialized workers are required.
	Centrifugation (Dw_4)	Good containment of bad odor emissions. Quick start and stop. High dry content of the dewatered sludge.	Specific maintenance required. Sand removal and sludge size reduction required. Need for highly qualified workers. High investment costs for medium-small plants.

Table 5. Strengths and limitations of all considered alternatives to carry out the composting and thermal drying treatments of the modeled SSTS.

Phase	Treatment	Strengths	Limitations
Phase 4 Composting (Co)		Good correction and fertilization capacity of the compost. Good level of stabilization. Compost can be stored better than sludge. Material recovery.	Need to use a filler. In some cases, high management costs. Production of bad odors.
Phase 5 Thermal drying (Td)		Very high dry content of the sludge. Very high reduction of volume and weight of sludge.	Need to dewater sludge before treating it.

The ANN model provides information about the necessity to perform (yes) or not perform (no) the operations included in these phases.

Finally, a set of three alternative operations was evaluated for the disposal of the treated sludges; the firsts two alternatives consist of spreading of the not-dewatered (Dp_1) or dewatered (Dp_2) sludge on the agricultural land. The third possible alternative, evaluated by the ANN model, consists of the incineration of the treated SS (Table 6).

The input parameters of the ANN model are plant capacity (PC), typology of secondary treatment (St) of the WWT, and the configuration of the SS treatment plant (CSp).

Table 6. Strengths and limitations of all considered alternatives to carry out the disposal treatments of the modeled SSTS.

Phase	Treatment	Strengths	Limitations
Phase 6 Disposal (Dp_i)	Spreading of not dewatered sludge on agricultural land (Dp_1)	Low investment costs. Material recovery. Soil correction and fertilization.	High transport and storage costs.
	Spreading of dewatered sludge on agricultural land (Dp_2)	Low transport and storage costs. Material recovery. Soil correction and fertilization.	High investment costs.
	Incineration (Dp_3)	Almost complete elimination of water. Almost complete stabilization. Suitable also for the treatment of fresh sludge. Energy recovery.	Very high investment and management costs. Very hard management. Need to strongly dewater the sludge before treating it. Need to manage fumes.

The PC is an input that mainly evaluates the economic feasibility of treatment for a specific plant. For small–medium plants, the choice of treatments with high management and investment costs is not economically sustainable; thus, a more convenient solution is provided. The St parameter allows us to consider the chemical–physical characteristics of the SS. The type of secondary treatment of the WW in the water line determines the features of the sludge produced that will be subjected to treatment. If St = 1, the SS derives from activated sludge secondary treatment and has physic–chemical characteristics that make it suitable for biological treatments. On the contrary, if St = 0, the SS derives from secondary chemical treatment, which uses lime as the primary reagent, and it is not suitable for biological treatments. Consistent with CSp parameters, two kinds of configurations of the treatment plant were evaluated: the first one was on a "single line", which means that the primary and the secondary SS were processed together on the same plant. The second one was identified as "separated line"; in this case, two different plants were adapted to treat the primary and secondary SS. Similarly, this parameter allows us to consider the different chemical–physical characteristics of the primary and secondary sludge mixed and separated, thus allowing us to identify the most suitable treatment.

In Table 7 are shown the typology and the range evaluated for each parameter. The ANN model output parameter consists of providing for each phase (i.e., Th_i, Sb_i, Dw_i, Co, Td, and Dp_i) the most effective strategy in economic terms.

Table 7. List of the input parameters of the ANN model.

Input Parameter	Unit of Measurement	Range	Typology
PC	(PE)	#1: [0, 5E3] #2: [5E3, 10E3] #3: [10E3, 20E3] #4: [20E3, 100E3] #5: [100E3, +∞]	Class
St	(#)	0: chemical treatment 1: activated sludge	Binary
CSp	(#)	0: single line 1: separated line	Binary

The output of the ANN model consists in an array "R" (Equation (1)), including six variables (r_i) defined in Equations (2)–(7).

$$R = \{r_1, r_2, r_3, r_4, r_5, r_6\} \quad (1)$$

where we have the following:

$$r_1 : \{Th_1, Th_2, Th_3, Th_4\} \tag{2}$$

$$r_2 : \{0, Sb_1, Sb_2, Sb_3, Sb_4\} \tag{3}$$

$$r_3 : \{0, Dw_1, Dw_2, Dw_3, Dw_4\} \tag{4}$$

$$r_4 : \{0, 1\} \tag{5}$$

$$r_5 : \{0, 1\} \tag{6}$$

$$r_6 : \{Dp_1, Dp_2, Dp_3\} \tag{7}$$

Each variable of the R-array represents a suitable alternative to adopt for each phase of the SSTS. The value "zero", in the case of r_2 and r_3, means that one or both treatments (i.e., stabilization and dewatering, respectively) could be not needed.

The ANN was adopted to support the model to provide, given a set of input parameters, the suitable alternative for each treatment step (output). A framework of the ANN model developed is provided in Figure 4. A sample of 300 data composed of input and output parameters was collected for the ANN design. The sample includes scientific researches and full-case studies, where, for each work conducted, the most effective strategy was suggested to manage the SS. In other words, the sample collects a set of input–output couples that "teach" the ANN how to reproduce, given a specific input set, the correct output.

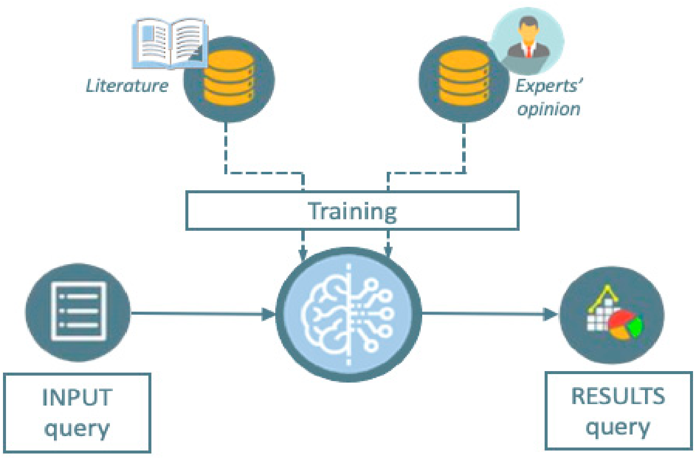

Figure 4. Framework of the ANN model adapted from Reference [28].

The sample adopted for the ANN training was extracted from the literature, validated, and integrated with other cases (around 10% of the sample size) collected by considering the experts' opinion. The set was split into training, validation, and test subsets, corresponding to the sizes of 210, 63, and 27 data, respectively. No extracted date were rejected by the experts. The approach developed is consistent with recurrent neural networks (RNN). A supervised learning algorithm based on the backpropagation (BP) was adopted, and a gradient-based optimization algorithm was used to update the network's weights to decrease the loss. The sigmoid and rectified linear unit (ReLU) activation functions were tested; the first provided more reliable predictions. However, it required data preprocessing based on the "along channel normalization" to improve the performance of the activation function. The trial-and-error approach was used to identify the ANN's proper architecture; the best fitness score was obtained by adopting an ANN with one hidden layer with 27 neurons, as outlined in Figure 5. Table 8 summarizes the main characteristics of the designed ANN.

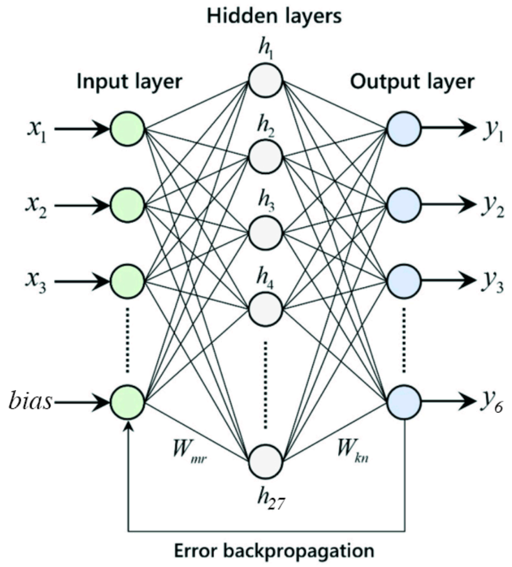

Figure 5. Architecture of the ANN with one input layer (x_i) with 3 nodes (i.e., PC, St, and Csp), one hidden layer (h_i) with 27 nodes, and one output layer (y_i) with six output nodes (i.e., r_1, r_2, r_3, r_4, r_5, and r_6) (adapted by Fernández-Cabán et al., "Predicting Roof Pressures on a Low-Rise Structure from Freestream Turbulence Using Artificial Neural Networks").

Table 8. Summary of the ANN characteristics.

Characteristic	Value
Dataset (Training, Validation, Testing)	210-63-27
Architecture (Input/Hidden/Output)	3-27-6
Structure	RNN
Activations	Sigmoid
Gradient update rules	Stochastic gradient descent

The ANN was designed and trained by adopting TensorFlow library in Python. ANN's learning process was performed on a MacBook equipped with a 1.6 GHz Intel Core i5 CPU and 4 GB RAM by using a plug-in of Microsoft Excel (i.e., Neuraltools). The average computational runtime was about 4 h and 58 min; around 1.25E8 epochs was required to minimize the loss.

The values assumed by PC affect the decision on the threshold of economic convenience with referring to aerobic and anaerobic digestion.

The results obtained considering all the constraints for each phase and the related considerations are shown in the next section.

4. Results and Discussions

The developed ANN model was tested on 20 possible scenarios, identified considering out-of-sample data. In other words, no data, already adopted to train, validate, and test the ANN was considered in this phase. The scenarios considered are generated on different combinations of the input values (i.e., PC, St, and Csp), while experts suggested the actual output values (i.e., r_1, r_2, r_3, r_4, r_5, and r_6). The values assumed from the predicted values of r_1 (Th_i), r_2 (Sb_i) and r_3 (Dw_i), given $r_6 = 1$ (Dp_1), excluding compositing and thermal drying treatment ($r_4 = r_5 = 0$), were compared with actual values corresponding to the recommended strategies for SS management. The graphs showed a good consistency of predicted values by ANN, as shown in Figure 6; in most cases, the ANN allows us to identify the same alternatives suggested by "experts" for each phase.

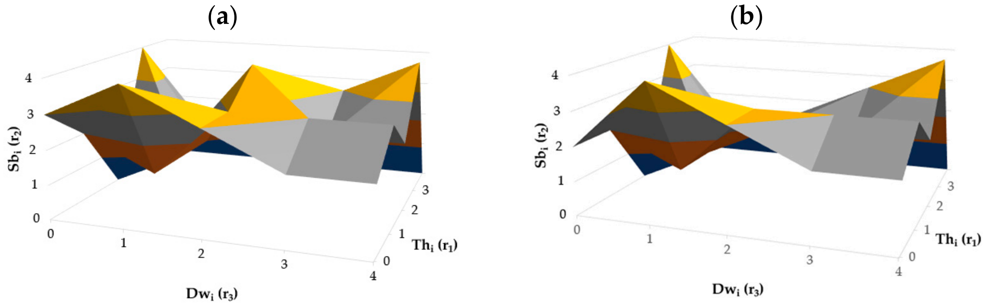

Figure 6. Comparison between predicted values (**a**) of output parameters (r_1, r_2, r_3) and actual values (**b**) of same parameters, evaluated in case of spreading r_6 = 0 (not-dewatered sludge on agricultural land) and r_4 = r_5 = 0.

The reliability of the designed ANN was tested on the same dataset, evaluating all output parameters obtained by considering different features. Most representative error parameters (i.e., Mean error (ME), Mean Absolute Deviation (MAD), Means Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE)), showed a good performance of the ANN to predict the target variables (Table 9). In all cases, the error is lower than twenty percent. The trend of ME and MAD showed that the ANN is not affected by systematic errors. Although the MSE and MAE are generally good (the average value is around 0.3), the performance decrees for the Dp_i prediction. Probably, the ANN has trouble identifying this value, since, in many cases, the same values of Dp_i are given for a different combination of the other features.

Table 9. Summary of the errors evaluated adopting the ANN on 20 cases identified by considering out-of-sample data.

Target	ME	MAD	MSE	MAE	MAPE (%)
Th_i	0.143	0.286	0.429	0.286	13.69
Sb_i	0.071	0.357	0.357	0.357	17.26
Dw_i	0.214	0.214	0.214	0.214	9.52
Co	−0.071	0.214	0.214	0.214	17.86
Td	0.071	0.214	0.214	0.214	14.29
Dp_i	0.357	0.500	0.643	0.500	16.67
Average	0.131	0.298	0.345	0.298	14.88

It is possible to claim that the average errors identified can exclude an overfitting problem. On the contrary, it should be better to evaluate the accuracy of the ANN adapting a Multi-Layer Perceptron (MLP) architecture. If, on the one hand, this could lead to an exponential increase in the running time, then, on the other hand, the performance could be drastically improved.

The introduced ANN model was interfaced with a query developed by Microsoft Office Visual Basic for Applications (VBA) version 7.1. Purely by way of example, two numerical cases were tested to validate the tool's effectiveness. The tool, as appears in the screenshots shown below (Figures 7 and 8), is handy, and a user-friendly query was designed. Only the information strictly required to query the ANN is included. In the first case, the ANN model to identify the more efficient SS treatment in a plant with PC of 12E3 PE was questioned, with a single line's configuration and providing a chemical treatment as secondary treatment. The screenshot shown below provides the representation of the input query of the tool (Figure 7).

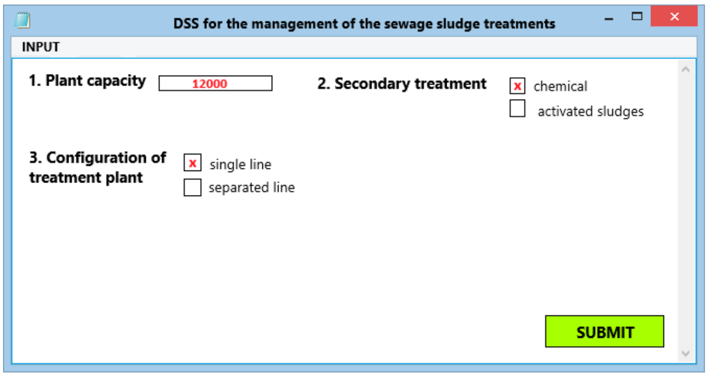

Figure 7. Screenshot of the VBA input query interfaced with the ANN model.

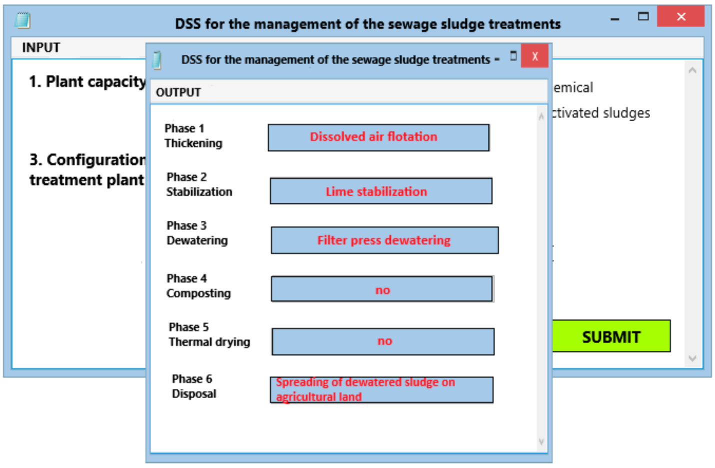

Figure 8. Screenshot of the VBA output query interfaced with the ANN model.

At the end of the elaboration process, the ANN model suggests a suitable alternative for each phase of SSTS (Figure 8). The ANN model suggests the following phases: dissolved air flotation (Phase 1), lime stabilization (Phase 2), filter press dewatering (Phase 3), no composting (Phase 4), no thermal drying (Phase 5), and finally, spreading of dewatered sludge on agriculture land for disposal (Phase 6).

In the second case, the SS treatment referred to a big plant (PC of 120E3 PE) with a single line's configuration, and providing an activated sludge as a secondary treatment to ANN model is required. Consistent with this case, the ANN model leads to different outputs. For this scenario, the ANN model suggests a gravity thickening, a stabilization by anaerobic digestion, a filter press dewatering, thermal drying, and incineration. This output is consistent with the results; indeed, anaerobic digestion and incineration, ensuring high energy recovery, are suggested.

Among the theoretical possible alternatives given by different combinations of the r_i-elements, the ANN model has been tested on 20 feasible scenarios, considering a set of input variables that stress the ANN model, evaluating cases very different from each other.

It is noted that, generally, for PC values included in the range of Class #1, the ANN model suggests carrying out thickening in sedimentation, stabilization, and disposal by spreading of not-dewatered SS on agricultural land. These suggestions are consistent with the WWTP dimensions considered where high investment costs are not recommended. Therefore, a stabilization treatment is suggested to ensure the SS's safe handling and disposal from an economic perspective. Generally, for PC included in the range of Classes #2 and #3, the ANN model suggests a thickening treatment in dedicated systems, followed by stabilization treatment, dewatering through natural systems, composting (in most cases), and disposal of dewatered SS in agricultural land. In these cases, the mechanical dewatering systems or anaerobic digestion systems are excluded by the ANN model, since they are considered not recommendable by experts. For PC included in the range of Class #4, stabilization by anaerobic digestion, if applicable, is recommended. Indeed, if, on the one hand, the anaerobic digestion treatment ensures high-performance in energy recovery, then, on the other hand, the investment and the running cost are very high. Finally, for PC included in the range of Class #5, the ANN model, in most cases, led to the adoption of dewatering treatment, followed by thermal drying and incineration.

5. Conclusions

The work conducted consisted of developing an ANN model that aims to identify the suitable SS treatment, based on a framework consisting of six steps and a predefined series of alternatives for each step, to suggest a most effective sludge-management strategy in economic terms. The developed ANN model was tested on 20 possible scenarios, identified considering out-of-sample data. The results showed the ANN model's effectiveness in supporting the decision-makers in identifying the SS treatment to be adopted. As it can be observed in Table 9, indeed, the application of the ANN to the 20 scenarios considered presents an average ME of 0.131 and a MAPE of 14.88%. The alternatives considered for each phase of the SS treatment are sustainable in economic terms. They are consistent with a circular economy approach, where the SS should be considered a resource more than a waste. The cases extracted from the literature review and the experts' opinion collected constituted a solid dataset to train the ANN to provide, by varying the input parameters, the most effective sludge management strategy in economic terms. Most of alternatives considered by ANN model allow for energy and/or matter recovery in line with the circular water value chain.

The tool allowing the implementation of the ANN model is user friendly and is free. The approach adopted lead to standardizing the decision-making process of the management of the SS. The management of which is generally considered too complex and with conflicting objectives and interests.

However, the ANN model requires a validation test on a full-real case study, as well as an upgrading of the possible alternatives included for each phase. Consistently whit this improvement, identifying the specific key performance indicators (KPIs) would quantify the performance of the solutions proposed for each scenario, under an economic and environmental perspective.

The results showed a good starting point to simplify the issues due to decision problems in this research field. In this context, the Industry 4.0 technologies could support the ANN model, providing a sensors network that improves the communication between stakeholders and plant manager to have continuous monitoring of the process status and by promoting a dynamical decision-making approach. In this case, the information on the transport and storage phases should be considered, with the aim to provide an exhaustive picture of the WWTP such as to ensure a minimal impact on the entire water value chain.

Considering the technical issues related to ANN model implementation, an improvement of the current works could consist of integrating VBA with a database in HTML5; thus, multiple applications could be used to support the ANN model.

Moreover, in this study are not considered aspects according to the concept of Triple Bottom Line (TBL), meaning the balance of economic, environmental, and social factors in corporate decision-making [29]. This represents a limit that could be challenged in future studies. Similarly, more alternatives for each phase concerning disposal should be considered to improve the effectiveness of the strategies proposed by the model.

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Abbreviations

Below a list of the abbreviations used in the manuscript is provided:

ANN	Artificial neural network
BP	Back-propagation
CH_4	Methane
Co	Composting
CO_2	Carbon dioxide
Csp	Configuration of the sewage sludge treatment plant
DEMATEL	Decision-making trial and an evaluation laboratory
Dp_1	Spreading of not dewatered sludge on agricultural land
Dp_2	Spreading of dewatered sludge on agricultural land
Dp_3	Incineration
Dp_i	Disposal
DSS	Decision support system
Dw_1	Drying beds dewatering
Dw_2	Belt press dewatering
Dw_3	Filter press dewatering
Dw_4	Centrifugation
Dw_i	Dewatering
GHG	Greenhouse gas
GRNN	Generalized regression neural network model
KPI	Key performance indicator
LCA	Life cycle assessment
LFPPFAHP	Logarithmic fuzzy preference programming based fuzzy analytic hierarchy process
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCDM	Multiple-criteria decision-making
ME	Mean Error
MSE	Mean Squared Error
N_2O	Nitrous oxide
PC	Plant capacity
PE	Population equivalent
RMSE	Root mean square error
Sb_1	Lime stabilization
Sb_2	Aerobic digestion
Sb_3	Anaerobic digestion
Sb_4	Anaerobic digestion for primary sludge and aerobic digestion for secondary sludge
Sb_i	Stabilization
SLNA	Systematic literature network analysis
SS	Sewage sludge
SSTS	Sewage sludge treatment system
St	Secondary treatment
Td	Thermal drying
Th_1	Thickening in sedimentation
Th_2	Gravity thickening
Th_3	Dissolved air flotation

Th_4	Gravity thickening for primary sludge and gravity belt thickening for secondary sludge
Th_i	Thickening
VBA	Visual Basic for Applications
W	Wavelet
WTE	Waste-to-energy
WW	Wastewater
WWT	Wastewater treatment
WWTP	Wastewater treatment plant

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