Athens Journal of Sciences- Volume 12, Issue 1, March 2025 – Pages 9-32

Predictive Modeling of Chemical Waste Generation in Healthcare Facilities: Enhancing Waste Management Strategies

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The escalating generation of chemical waste in healthcare facilities is a pressing concern, particularly during rapidly spreading epidemics. This study proposes a system dynamics model to predict hospital chemical-waste generation rates. The model incorporates various variables, such as patient arrival and departure rates, to provide accurate estimations of waste generation. A case study conducted at a hospital validates and demonstrates the proposed model's practical application. The findings reveal that specific departments, such as Main Operations, Obstetrics, and Catheter, significantly influence healthcare chemical-waste generation rates. Additionally, the Tissue Department plays a substantial role. This research has two important implications. Firstly, it offers valuable insights into the complex factors affecting waste generation in healthcare facilities, identifying the departments that contribute most to the problem. Secondly, it provides waste management departments with a insights for capacity planning, scheduling, and resource allocation. Hospitals can enhance their waste management practices, leading to improved environmental sustainability and better public health outcomes. This study's ability to anticipate chemical waste generation and drive the development of comprehensive and long-term waste management programs is highlighted by its identification of the most significant departments in generating chemical waste. This study blends predictive intelligence with pragmatic insights, emerging as a crucial instrument for tackling the severe difficulties posed by the rising flow of chemical waste. It ultimately protects both individual well-being and the balance of the ecosystem.

Keywords: *system dynamics, chemical waste, healthcare facilities*

Introduction

Human activities, modern lifestyles, and everyday consumption habits have resulted in massive waste over the last few decades (Oweis et al. 2005). The waste produced by activities at healthcare facilities carries a greater risk of illness and harm than other waste types (Ciplak and Barton 2012). Assessing and prioritizing healthcare

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https://doi.org/10.30958/ajs.12-1-1 doi=10.30958/ajs.12-1-1

waste hazards is a paramount problem. Thus, highlighting the importance of waste management strategies, policies, and corrective actions to mitigate the adverse effects of healthcare waste is critical (Navazeshkhah et al. 2019, ALMashaqbeh and ALKhamisi 2023). The waste released in healthcare facilities can be divided into general and hazardous waste (Kerdsuwan and Laohalidanond, 2015). Most healthcare waste (75–90%) is non-risk (also known as general waste) (Eleyan et al. 2013). The remaining 10–25% of healthcare facility waste is considered infectious and dangerous, posing several health hazards (Chaerul et al. 2008, Mol et al. 2022), and should be carefully managed and disposed according to (Neves et al. 2022). Waste can be considered hazardous if it checks one or more characteristics: ignitability, corrosivity, reactivity, and toxicity (Polprasert and Liyanage 1996). This study will focus on Chemical healthcare waste, which is hazardous since it is an ignitable type of waste.

The main types of chemical waste in healthcare facilities are categorized into formaldehyde, photographic fixing, and developing solutions; solvent wastes that contain halogenated and non-halogenated compounds; and wastes from materials with high heavy-metal contents (Ciplak and Barton 2012, Mohiuddin 2018, Laz et al. 2019).

Formaldehyde is considered a substantial chemical waste source, used in pathology, autopsy, dialysis, embalming, and nursing facilities, as well as to clean and disinfect equipment (such as hemodialysis or surgical equipment), preserve specimens, and disinfect liquid infectious waste (World Health Organization 2014). Formaldehyde is a virtually colorless gas with an overpowering stench at room temperature. In markets, formaldehyde is often sold as 30 to 50 percent (by weight) aqueous solutions of the hydrated form, also known as formalin (Lyapina 2012). It is considered a very toxic material, putting the lives of those who deal with it at risk. Safe disposal of this toxic waste is a requirement; thus, predicting the waste volume of such chemical material needs to be investigated. This helps to manage the waste-disposing system more efficiently to avoid excessive contact with this toxic chemical.

Increasing the potential risk associated with chemical healthcare waste is the existing gap in knowledge, training, and consciousness among healthcare personnel about safe chemical healthcare management; despite the availability of clearly stated standards, it leads to unsafe practices, exposing both health and the environment to potential hazards (Sharma 2010).

Due to the risks posed by these types of waste, additional care must be taken in collecting, storing, transmitting, and disposing of chemical healthcare waste. The waste management system is a combination of these four waste processing cycles. In waste management analyses, the amount of future healthcare waste is crucial. The amount of waste generated must be known with great precision to form an accurate strategy for disposal. This strategy is based on estimating the volume of the waste in terms of all related variants, including the dynamism.

Our study focuses on Chemical healthcare waste, which is hazardous since it is an ignitable type of waste. Predicting the amount of healthcare waste generation rate is vital to an efficient hospital's planning and procedure. Therefore, this paper aims to develop a prediction model to anticipate the future status of chemical waste generation in hospitals. The model will be validated and studied based on a case study; thus, the current study will be conducted in a hospital.

The theoretical and practical contributions in developing this model for chemical waste prediction in healthcare facilities can be summarized as follows.

1. Introducing a model for chemical waste generated amounts prediction in healthcare facilitates.
2. Identifying the system's complexity by investigating the factors affecting chemical waste and their relations.
3. As a practical implication, the developed model helps the waste management department to plan recycling operations and resource allocation. Starting recycling activities is a positive start toward tackling the issues related with hazardous waste and environmental damage (McCoy et al. 2017).

Literature Review

Various methodologies were used to predict hazardous waste in general, particularly healthcare chemical waste. For example, the multiple linear regression (MLR) technique was used in some studies, such as (Thakur and Ramesh 2018, Golbaz et al. 2019, Çetinkaya et al. 2020). Machine learning approaches such as artificial neural networks (ANN), fuzzy logic-artificial neural networks (ANFIS), and support vector regression (SVM) have evolved and been adopted in such areas. They have grown prominent in recent years due to their high flexibility and demonstrated prediction skills (Golbaz et al. 2019). Some studies used Artificial neural networks (ANN), including (Karpušenkaitė et al. 2016). Other studies used Autoregressive Integrated Moving Average (ARIMA), such as (Ceylan et al. 2020). In some studies, researchers included both artificial neural networks (ANNs) and multiple linear regression (MLR) predictor models such as (Jahandideh et al. 2009). Support Vector Regression (SVR) and Grey Modelling (1,1) were also used in many studies.

In a study conducted on the European Union (EU) in 2018, the general regression neural network (GRNN), which is a form of artificial neural network (ANN), is used to predict the annual quantities of hazardous chemical and healthcare waste. Their study has considered chemical waste, unlike many other studies that predicted the amounts of hazardous waste in healthcare facilities. Although this study predicts the quantities of waste produced, it generally studies chemical waste. Still, it is not associated with healthcare activities and does not examine the different types of healthcare hazardous waste separately (Adamović et al. 2018).

More studies in different systems considered simulating toxic waste production (N. et al. 2010) illustrate how computer-based modeling is used to track and manage environmental impacts. Such modeling can provide insights into complex interactions within ecosystems and help avoid the health and environmental risks associated with insufficient waste disposal procedures, resulting in a cleaner and safer environment.

One of the main methods used in waste prediction is System Dynamics (SD). It is a modeling methodology introduced by "Jay Forrester" in the 1960s based on feedback, a substantial element in analyzing systems. It models complex systems and allows easier decision-making and conceptualization when evaluating different scenarios. System Dynamics can adequately track the impacts of changes in subsystems and their relationships and represent and express them (Chaerul et al. 2008). System dynamics is introduced as a modeling and simulation tool for long-term decision-making analysis of industrial management challenges. Forrester also concluded that the mathematical concepts of control theory do not apply to managed systems since they are significantly more complex than engineering challenges. As a result, the final stage of Forrester's intellectual achievement was to design the structure of specialized computer simulation languages so that system dynamics computations could be conducted quickly and efficiently (Coyle 1997). The importance of simulation models rests in their adaptability and capacity to handle complex system behavioral features.

Many studies have used system dynamics to represent waste management systems, but using prediction models to represent chemical healthcare waste is rarely found. For example, researchers (Ciplak and Barton 2012) used SD to develop a model to help select and plan future treatment capacity. The case study location was Istanbul, Turkey. Observations and interviews were done in Istanbul over three months to discover the factors driving healthcare waste generation. A system dynamics model was used to develop a healthcare waste management model using the software package Vensim® PLE Plus. Authors (Zanjani et al. 2012) implemented the system dynamics method in solid waste management. Other studies, like (Singh et al. 2022), investigated various socioeconomic and environmental parameters on medical waste generation.

In Chaerul et al. (2008), using the Stella® software package, a hospital waste management model based on system dynamics was developed to determine the interaction among variables in the system. The city of Jakarta, Indonesia, was chosen as a case study. The main variables considered in their studies model were the number of hospital beds and the NIMBY (not in my backyard) syndrome, which suggests that individuals support a project as long as it is not in their backyard (Uji et al. 2021). The main idea of this study is that segregating medical waste and infectious waste treatment before disposal must be done correctly by hospital management.

In Al-Khatib et al. (2016), the researchers focus on the current state of waste generation without anticipating and predicting future generation rates or waste treatment and disposal costs. Although the model represents medical waste, it uses different variables than the ones this study uses, and the type of waste predicted is more general than what this study considers. The variables used in their study included inpatients and outpatients in different hospitals. However, in addition to inpatients and outpatients, our current study had detailed data on each floor and unit. Our model also explicitly predicts the chemical waste generation rate and the type of floor's influence on the generation rates.

In Eleyan et al. (2013), the researchers used system dynamics to anticipate generated medical and solid waste in a developing metropolitan environment. The study suggests that when traditional statistical least-squared regression methods cannot predict the generation of these types of wastes, a new forecasting approach may cover a variety of possible causative models and track inevitable uncertainties by separating the wastes into categories (metals, cardboard, paper, textiles, plastics, glass, and other materials).

Understanding the dynamics of waste generation is paramount in the pursuit of efficient waste management. Previous studies have primarily focused on general hazardous waste prediction and healthcare waste in broader terms. Our study, however, delves into the specific realm of healthcare chemical waste due to its inherent toxicity, necessitating meticulous handling and disposal strategies. To achieve this, we aim to construct a prediction model using the System Dynamics (SD) approach, allowing for precise volume forecasts and informed waste management strategies. This modeling approach considers various factors, including the type of department treatment indicated by floors, providing comprehensive insights into chemical waste generation rates. We emphasize the need for dedicated modeling by distinctly addressing healthcare chemical waste, considering the unique characteristics and associated risks that demand specialized disposal strategies. Integrating our predictive model into waste management practices will empower healthcare facilities to efficiently plan resources and manage hazardous waste more safely and sustainably.

Methodology

This section presents the model development framework of the chemical waste prediction model using the systems dynamics approach. It also includes the causal loop diagram that leads to the development of the final systems dynamics model. This diagram considers the patients' population dynamics, including the impact of the arrival and departure rates of patients, leading to the number of hospital patients and the waste weights collected from each floor in the hospital.

The following section presents the development of the causal loop diagram.

Causal Loop Diagram

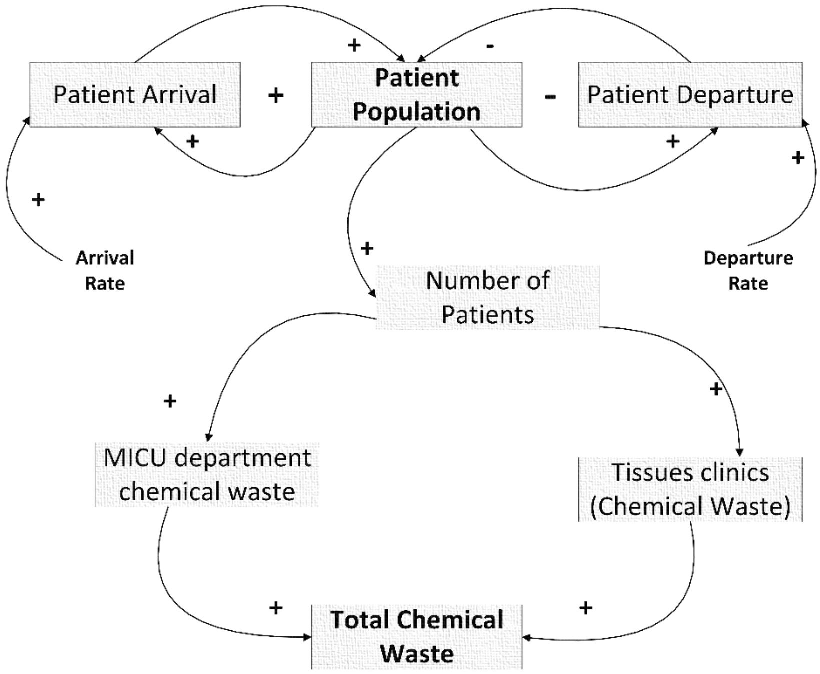
The first step in developing an SD model is to create the causal loop diagram. The causal-loop diagrams were not usually used in early system dynamics modeling. However, such diagrams provide a way to make system dynamics more approachable to a broader audience. This step is also referred to as systems thinking.

The diagram represents the causal relationships between the relevant variables (factors). It is a representation of the main feedback using arrows and elements (casual links) that connect the signs, either positive (+) or negative (-), that represents the state of the relationship between different elements. If the symbol is positive (+), all effects head in the same direction. As one aspect increases, the other increases as well. A negative (-) sign indicates that the two elements are heading in opposite directions, with one rising and the other declining.

After that, depending on the number of positive (+) or negative (-) signs in the loop, the entire loop is given a sign, either positive (+) or negative (-). The loop is given a positive (+) sign if the number of negative (-) signs is even, indicating that the system is unstable. If the number is odd, the loop is given a negative (-) sign, indicating that it is in equilibrium.

The causal loop diagram is built by determining the variables intended to be used in the model. A sample of the causal loop diagram created is shown in Figure 1. As shown in Figure 1, the patients' arrival and departure rates affect the patient population. This population affects the arrivals and departures numbers in return, which is called a feedback loop. The population affects the number of patients in the case study hospital, as the number increases when the population increases. The chemical waste is directly related to the net number of patients.

Figure 1. *Causal Loop Diagram - Sample from*



The chemical waste quantities data was obtained from the hospital records. A sample of one year for the waste quantities was obtained, including the floor name, day of collection, type of waste (chemical solid/ chemical formaldehyde), and weights in Kg. The total waste (chemical solid/ chemical formaldehyde) for each floor in the hospital and outpatient clinics is calculated using the collected data to find the rate each floor produces in (kg/bed/day).

After developing this diagram, the next stage is developing the system dynamics model, which is introduced in the next section.

System Dynamics Model

The system dynamics model was developed to predict the amount of chemical waste the hospital generates, explicitly focusing on formalin waste produced by surgical floors. This chemical material is primarily used as an antiseptic, disinfectant, and histology fixative, and it is toxic to the human body if it is misused.

The model considers the number of patients in the hospital as the primary driver of waste production on each floor, which is calculated using previously explained equations. The "population" stock is directly linked to the number of arrivals and departures of patients, which is determined based on the patients' population. Each floor and department in the hospital has a specific waste production rate per patient, which is included in an equation connecting these variables to produce an accurate prediction of the total chemical waste generated. The model accounts for the fact that not all floors in the hospital create all types of waste, and only the floors that generate the chosen kind of waste (solid and Formalin) are included.

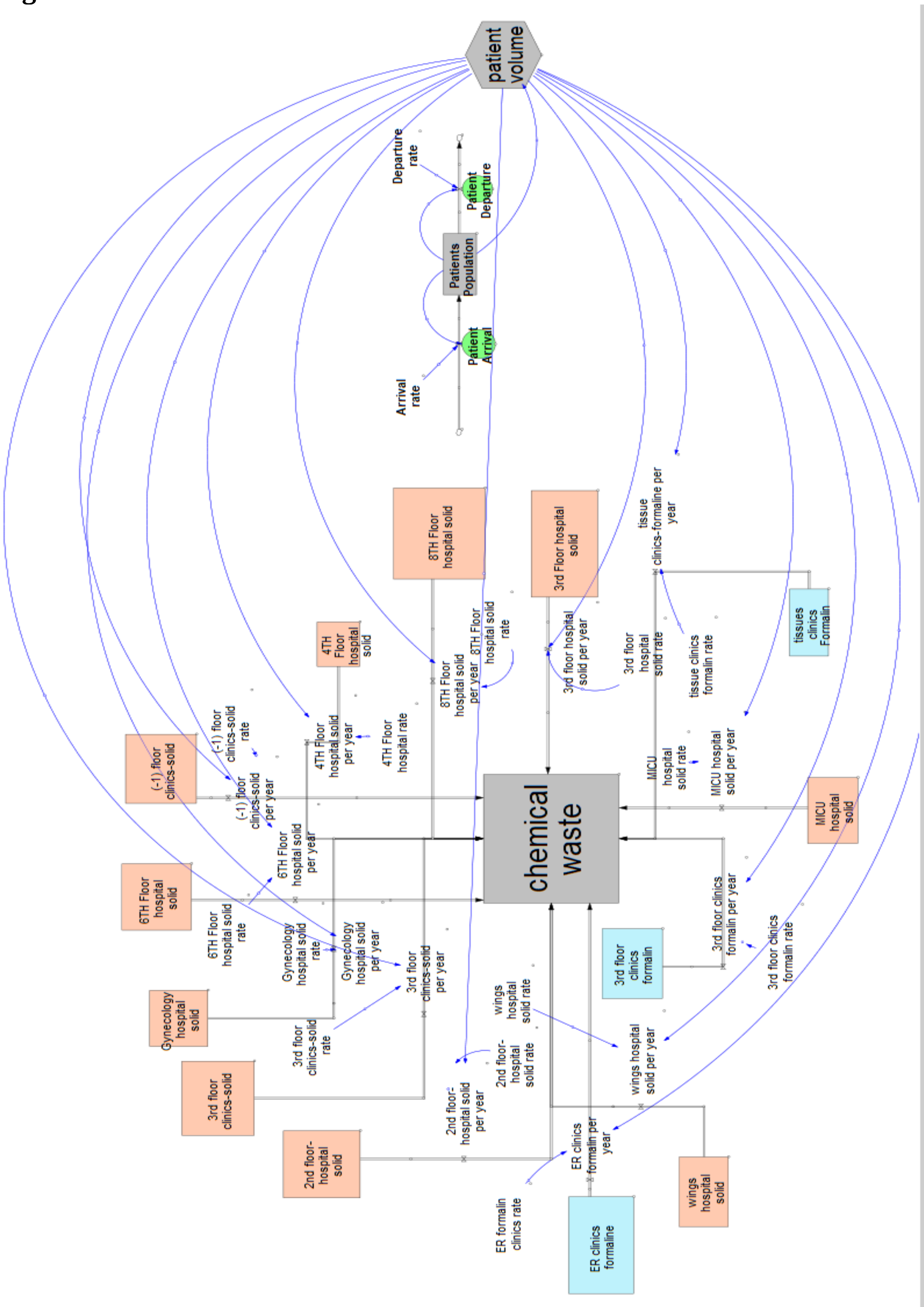
The model employs orange squares to represent the stock of solid chemical waste produced and blue squares to represent the stock of formalin chemical waste produced by specific floors in the hospital. Considering each floor's generation rates, these stocks are summed and directed into a single "Chemical waste." Each floor has a blue arrow directed toward it, originating from the "Patient volume" variable representing the number of patients in the hospital. This arrow represents the flow of patients into that particular floor and their corresponding impact on the production of chemical waste. The construction of this system dynamics model is illustrated in Figure 2. The system includes a stock for the chemical waste on each floor, directed towards the total chemical waste stock via an arrow with flow in the middle. Each floor is also associated with a variable connected to the waste generation rate, depicted by a blue connector arrow.

The hospital floors represented in the model consist of different departments, each with a distinct function. Table 1presents the departments present on each floor. The idea is determining which floors and departments produce the most chemical waste.

Table 1. *Departments of Every Floor in the Hospital that are Considered in this Study*

Floor Name	**Departments**
3rd floor clinics (outpatients)	Dialysis, Blood bank, clinical laboratory, gynecology clinics.
-1 floor clinics (outpatients)	Blood disease, Nerve clinics, psychology, diabetes, and pediatrics clinics.
2nd-floor Hospital (Inpatients)	Surgery patient's rooms.
3rd-floor Hospital (Inpatients)	Pre-operative rooms and ICU.
4th-floor Hospital (Inpatients)	Surgery patient's rooms.
6th-floor Hospital (Inpatients)	Internal Medicine Department and Pulmonary Function Laboratories
8th-floor Hospital (Inpatients)	Pediatrics.
ER clinics (outpatients)	ER clinics
Tissues clinics (outpatients)	Tissues clinics
Gynecology hospital (Inpatients)	Gynecology department at the hospital
MICU hospital (Inpatients)	MICU of the hospital
Wings Hospital (Inpatients)	Wings of the hospital

Figure 2. *Chemical Waste SD Model*



Model Mathematical Relationships

In order to define the relationships between the system dynamics components, mathematical equations in the stock-and-flow diagrams are used to represent the feedback structure. All the parameters and variables are calculated using the equations explained below.

– **Patient Population:**

Patient population **(**Ƥ**)** is composed of the number of patient arrival influenced by the arrival rate **(**$\boldsymbol{\Gamma_A}$**)** and the number of patient departures influenced by the departure rate **(** $\boldsymbol{\Gamma_D}$**)**. Arrivals are calculated by multiplying the patients' population **(**Ƥ**)** by the arrival rate **(**$\boldsymbol{\Gamma_A}$**);** similarly, departures are calculated by multiplying the patient population **(**Ƥ**)** by the departure rate **(** $\boldsymbol{\Gamma_D}$**) as shown in equations** (1-3).

$$\boldsymbol{P_t = P_{t-1}} + (\boldsymbol{Arrivals - Departure}) \quad (1)$$
$$\mathbf{Arrivals} = Ƥ \times \boldsymbol{\Gamma_A} \quad (2)$$
$$\mathbf{Departures} = Ƥ \times \boldsymbol{\Gamma_D} \quad (3)$$

– **The mean amount of waste for each floor (kg/day):**

The mean amount of waste on each floor per day is calculated by adding all waste weights (Kg) for a specific floor and dividing it by the total number of days, as shown in Equation (4).

$$\bar{X} = \frac{\sum \boldsymbol{X}}{\boldsymbol{N}} \quad (4)$$

where $\bar{X}$ (Kg/day) represents the mean waste weight in (Kg) of each floor, $\sum \boldsymbol{X}$ is the total waste weight (Kg) produced from the floor, and N is the total number of days of the case study duration (day). This Equation is repeated to all floors before being incorporated into the rate equation.

– **Rate of waste generation for each floor (Kg/bed/day):**

The chemical (formalin/solid) waste generation rate on each floor is essential in developing the system dynamics model. According to the data available, the waste generation rate ($\boldsymbol{\Gamma_p}$) (Kg/bed/day) is calculated by dividing the mean amount of waste for a floor ($\bar{X}$) (Kg/day) by the total number of patients who are treated in the case study hospital ($\sum \boldsymbol{p}$) (bed). Equation (5)

$$\boldsymbol{\Gamma_p} = \frac{\bar{\boldsymbol{X}}}{\sum \boldsymbol{p}} \quad (5)$$

Another essential formula used later in the results is the percentage of change ($\%\boldsymbol{\Delta}$) used in the sensitivity analysis. This value is calculated by dividing the original value of either cost or weight ($\boldsymbol{V_O}$) with the new value resulting from doubling one variable ($\boldsymbol{V_N}$), Equation 6.

$$\%\boldsymbol{\Delta} = \frac{\boldsymbol{V_N - V_O}}{\boldsymbol{V_O}} * \mathbf{100}\% \quad (6)$$

– **Accelerated rate of change**

The enhanced rate of change was determined by subtracting the prevailing rate from the preceding rate and then accelerating by a decadal amplification factor, see Equation (7).

$$\boldsymbol{\alpha} = (\%\boldsymbol{\Delta_N} - \%\boldsymbol{\Delta_O}) \times \boldsymbol{\lambda} \quad (7)$$

where "α" represents the accelerated rate of change, "λ" represents the amplification factor, and "$(\%\boldsymbol{\Delta}_{\boldsymbol{N}} - \%\boldsymbol{\Delta}_{\boldsymbol{O}})$" represents the annual disparity in alterations.

Recognizing the significant increase in chemical waste generation is crucial for resource allocation and effective waste management planning in healthcare facilities. It also helps evaluate environmental impacts and promote sustainable waste solutions. Analyzing the rate of change addresses health and safety issues and ensures compliance **with chemical waste management** regulations, preventing legal and operational complications.

Case Study

Data Collection

This case study was conducted at the University of Jordan Hospital in Amman, Jordan, over one year (March 2021 to March 2022). The hazardous waste generated at the hospital was categorized into two types: medical waste and chemical waste, which were then collected and weighed by the staff from the medical waste unit on each floor, including the outpatient clinics.

Having a medical waste treatment unit and being one of the largest hospitals in Jordan, this healthcare facility was an ideal place to perform this study. The hazardous waste unit also collected waste data from each department separately, providing valuable information for the study. The data considered in this case study included the weights of chemical waste generated over one year, the number of hospital patients, and the patient population considering the number of arrivals and departures during the same period. Table 2presents the data used to predict the total amount of chemical waste the hospital will generate over the next ten years.

Table 2. *Input Data (Rate of Change and Initial Weights for Each Floor)*

Floors	Rate of change	Chemical waste weights (Kg)
UG_C-S	6.39E-05	44.7
$2G_H$-S	3.52E-05	24.65
$3G_C$-F	0.0004432	310.2
3 G_C-S	0.0004137	289.55
3 G_H-S	6.43E-06	4.5
$4G_H$-S	3.76E-05	26.35
$6G_H$-S	8.98E-05	62.85
$8G_H$-S	2.14E-06	1.5
ER_C F	2.67E-05	18.7
Gynecology $_H$ S	3.71E-06	2.6
$MICU_H$ S	9.50E-06	6.15
tissue G_C F	0.0022505	1575.65
wings $_H$ S	5.86E-06	4.1

Validation and Verification

The system dynamics model was verified by testing and evaluating if the model was implemented correctly. The model's compatibility with the actual system structure and the entered data were checked by experts from the hospital. The verification was done by walking through the model and checking the flow logic. Moreover, Since Vensim software offers logical checks, the model's verification is emphasized when the model is executed. When there are any dimensional inconsistencies or mistakes made when creating the model equations, the software discloses an error that prohibits the model from running.

One of the challenges in using simulated data for scientific research is the possibility of inaccuracies in the mathematical models that support the simulations. These mistakes can produce incorrect or misleading findings (Pavin and Knežević 2023), this can only be solved by validating the model.The validation compares the model's results with the actual system results (data). The case study data was collected from March/2021 to March/2022. Therefore, to validate the model, a comparison was made between the predicted results of the total chemical waste produced and the true results provided by the hospital for the following month (May/2022). Total chemical waste weight predicted for the next year by the model is 2402.64 Kg/year, which is 200.22 kg/month on average. According to the hazardous waste unit staff at the hospital for May/2022, the actual value was 194.3 Kg, which indicates an error of 2.95%. This percentage is assumed to be acceptable, indicating the model's validity.

Model Run

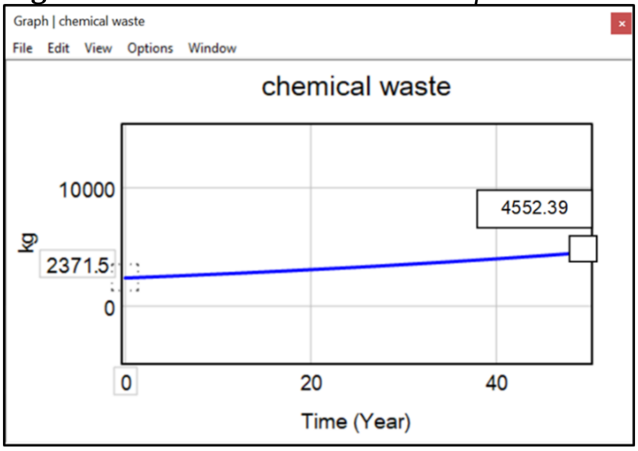
After the developed system dynamics model has been run, the predicted values of the total chemical waste, the total number of patients in the hospital, and the number of arrivals and departures are shown in Table 3. It shows that the total chemical waste increases as the patient population increases.

Table 3. *The Prediction Results for the Next Ten Years*

Year	Patient Population	Number of Arrivals	Number of Departures	Number of patients in the hospital	Total Chemical waste (Kg)
2021	10300000	171268	36050	699925	2371.5
2022	10435200	173517	36523	709114	2402.64
2023	10572200	175795	37002	718423	2434.18
2024	10711000	178103	37488	727854	2466.13
2025	10851600	180441	37980	737410	2498.51
2026	10994100	182810	38479	747090	2531.31
2027	11138400	185209	38984	756898	2564.54
2028	11284600	187641	39496	766835	2598.21
2029	11432800	190104	40014	776902	2632.32
2030	11582900	192600	40540	787101	2666.87
2031	11734900	195128	41072	797434	2701.89

Figure 3 shows predicted chemical waste quantities for the next 50 years. It indicates the increasing rate in the produced amounts of waste depending on the change in patients' population, rate of departures and arrivals, and the number of patients in the hospital.

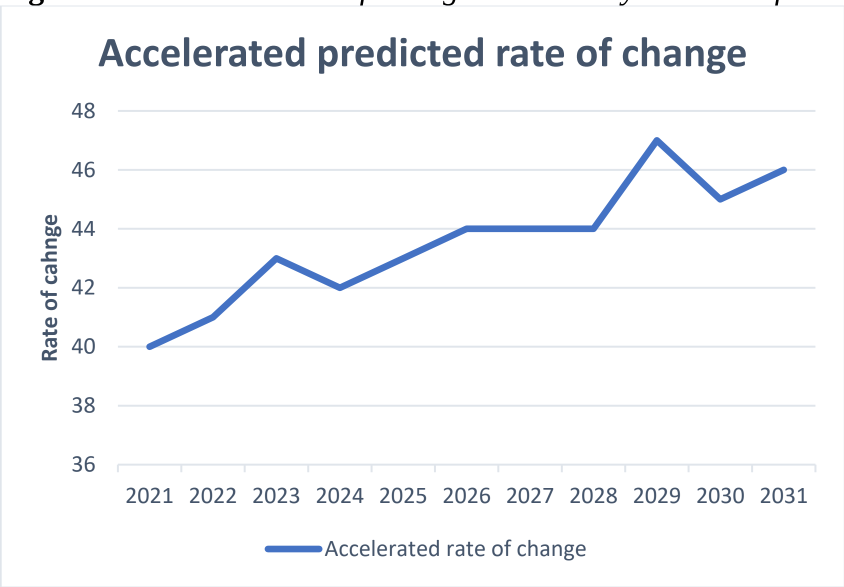
Figure 3. *Chemical Waste Prediction for the Next 50 Years*



Accelerated predicted Rate of Change

The accelerated rate of change predicted by the model for the next decade, Using an amplification factor of 10, can be represented in Figure 4.

Figure 4. *Accelerated Rate of Change Predicted by the Model for the Next Decade*



The rate change sequence resulting from the model, spanning from 0.4 to 0.47 within the initial decade, demonstrates the dynamic effect of numerous parameters on generation rates. Different variations emphasize the complex interplay of other elements, such as the number of arrivals and departures and the comprehensive array of distinct departments considered on a substantial scale, illustrating the wide range of their influence on the overall rate of change. The data emphasizes the importance of considering a wide range of factors when studying variations in generation rates, emphasizing the complexities of the observed patterns.

Experimental Design

This section aims to design and run different scenarios to identify the impact of changing various parameters of the waste prediction model on its robustness.

First Scenario: Increase the Usage of Formalin in Medical Procedures for a New Surgical Breakthrough

This scenario discusses the impact of increasing the amounts of Formalin usage in a surgical breakthrough on the quantity of Formalin wasted. As shown in Figure 5, the difference in the chemical waste generated is significant compared to the previously predicted value by the developed model. For example, the initial expected value for the second year is 1,954 Kg, while the new predicted value of the scenario is approximately 3,909 Kg. Although the new value is significantly higher, this prediction would be helpful in terms of redesigning the chemical waste units, especially the Formalin saving unit, because Formalin is considered a very poisonous material and harmful to the environment.

Figure 5. *Scenario I Vs Original Model Predictions*

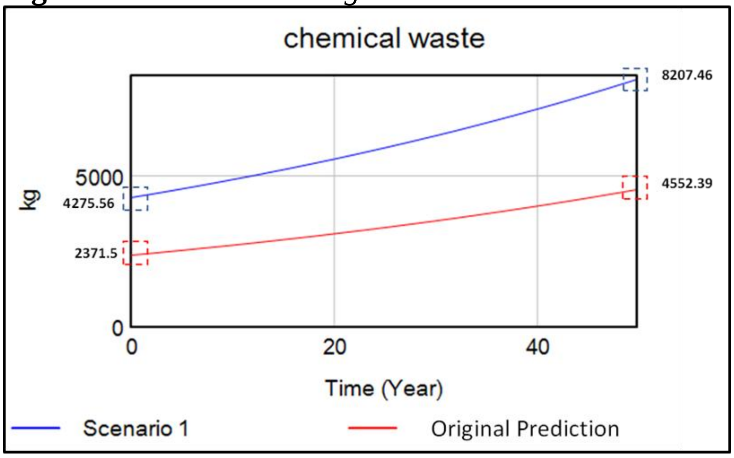


Figure 5 shows a difference between the original prediction results obtained by running the developed SD model and the first scenario results. This is attributed to the fact that by increasing the waste rate of Formalin, the difference between them will increase. The modified rates and the obtained predicted amounts of Formalin are shown in Table 4. Also, a comparison is made between the original prediction and the one resulting from the scenario.

Table 4. *Scenario I Detailed Results*

Years	3rd-floor clinics formalin rate: Scenario 1	3rd floor clinics formalin rate: Original	ER formalin clinics rate: Scenario 1	ER formalin clinics rate: Original	Tissue clinics formalin rate: Scenario 1	Tissue clinics formalin rate: Original
	0.000886	*0.000443*	*5.34E-05*	*2.67E-05*	*0.004501*	*0.00225*
	Predicted weights for each floor					
2021	*620.4*	*310.2*	*37.4*	*18.7*	*3150.3*	*1575.2*
2022	*628.5*	*314.3*	*37.9*	*18.9*	*3191.7*	*1595.8*
2023	*636.8*	*318.4*	*38.34*	*19.2*	*3233.6*	*1616.8*
2024	*645.2*	*322.6*	*38.9*	*19.4*	*3276.0*	*1638.0*
2025	*653.6*	*326.8*	*39.4*	*19.7*	*3319.0*	*1659.5*
2026	*662.2*	*331.1*	*39.9*	*20.0*	*3362.6*	*1681.3*
2027	*670.9*	*335.5*	*40.4*	*20.2*	*3406.7*	*1703.4*
2028	*679.7*	*339.9*	*40.9*	*20.5*	*3451.5*	*1725.7*
2029	*688.6*	*344.3*	*41.5*	*20.8*	*3496.8*	*1748.4*
2030	*697.7*	*348.8*	*42.1*	*21.0*	*3542.7*	*1771.3*
2031	*706.8*	*353.4*	*42.6*	*21.3*	*3589.2*	*1794.6*

Scenario II: Increasing the Production of Solid Chemical Waste

In the second scenario, only the rates of the floors that produce solid chemical waste are increased. The SD model is then simulated after changing the rates for every floor to identify the impact of waste rate on the predicted waste volume. Figure 6 compares the amount of waste expected of the original and the second scenario for the next 50 years.

Figure 6. *Scenario II Vs. Original Model Predictions*

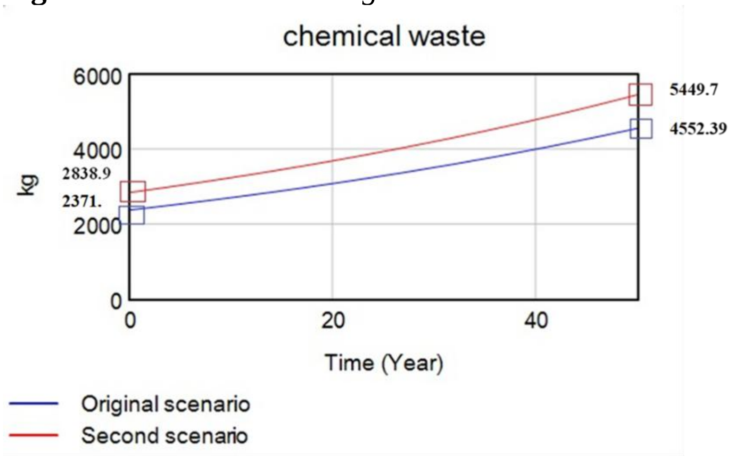


Table 3shows the waste volume predicted in the second scenario for each floor as well as the doubled rates that were implemented in the model.

Table 5. *The Rates and Predicted Amount of Each Floor for the Second Scenario*

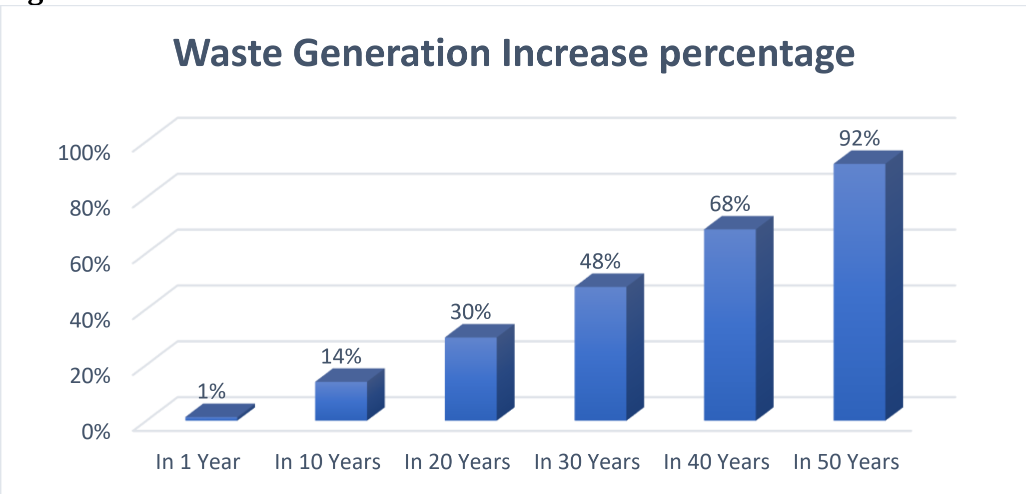
Years	(-1) floor clinics-solid rate.	2nd floor. Hospital solid rate.	3rd floor clinics solid rate.	3rd floor hospital solid rate.	4TH Floor hospital rate.	6TH Floor Hospital solid rate.	8TH Floor hospital solid rate	Gynecology hospital solid rate	MICU hospital solid rate.	Wings Hospital's solid rate
	0.000127728	*7.04E-05*	*0.000827374*	*1.29E-05*	*7.53E-05*	*0.000179591*	*4.29E-06*	*7.43E-06*	*1.90E-05*	*1.17E-05*
	Predicted weights for each floor									
2021	*89.4*	*49.3*	*579.1*	*9.0*	*52.7*	*125.7*	*3.0*	*5.2*	*13.3*	*8.2*
2022	*90.6*	*49.9*	*586.7*	*9.1*	*53.3*	*127.3*	*3.0*	*5.2*	*13.4*	*8.3*
2023	*91.7*	*50.6*	*594.4*	*9.2*	*54.0*	*129.0*	*3.0*	*5.3*	*13.6*	*8.4*
2024	*92.9*	*51.2*	*602.2*	*9.3*	*54.8*	*130.7*	*3.1*	*5.4*	*13.8*	*8.5*
2025	*94.1*	*51.9*	*610.1*	*9.4*	*55.5*	*132.4*	*3.1*	*5.4*	*14.0*	*8.6*
2026	*95.4*	*52.6*	*618.1*	*9.6*	*56.2*	*134.1*	*3.2*	*5.5*	*14.1*	*8.7*
2027	*96.6*	*53.3*	*626.2*	*9.7*	*56.9*	*135.9*	*3.2*	*5.6*	*14.3*	*8.8*
2028	*97.9*	*54.0*	*634.4*	*9.8*	*57.7*	*137.7*	*3.2*	*5.6*	*14.5*	*8.9*
2029	*99.2*	*54.7*	*642.7*	*9.9*	*58.4*	*139.5*	*3.3*	*5.7*	*14.7*	*9.1*
2030	*100.5*	*55.4*	*651.2*	*10.1*	*59.2*	*141.3*	*3.3*	*5.8*	*14.9*	*9.2*
2031	*101.8*	*56.1*	*659.7*	*10.2*	*60.0*	*143.2*	*3.4*	*5.9*	*15.1*	*9.3*

Escalation of Waste Production Percentage

The exponential trend of increased waste generation creates a persuasive picture of the evolving risk when addressing chemical waste.

Figure ***6*** 6 shows the estimated increase in chemical waste production in the next 50 years.

Figure 7. *The Estimated Increase in Chemical Waste Production in the Next 50 Years*



In less than a decade, a 14% rise in the output of this chemical waste is predicted. This pace of change, however, accelerates substantially, striking 30% over two decades and nearly doubling to 48% in the following ten years. The situation's urgency becomes apparent as time passes, with the percentage rise reaching 68% after 40 years. Most importantly, the figures demonstrate a stunning 92% rise in chemical medical waste creation over 50 years.

Conclusion

The generation of healthcare chemical waste has significantly increased in recent decades due to global population growth and the expanded use of chemicals in the medical field, particularly in laboratories. This escalating trend poses substantial risks to human life if the waste is improperly managed and disposed of. A system dynamics (SD) model was developed to forecast the volume of chemical waste generated in a healthcare facility, considering patient arrival and departure rates across different departments. System dynamics is a powerful modeling approach that enables an understanding of complex, dynamic systems and their interdependencies.

The University of Jordan Hospital was chosen as a case study to validate the effectiveness of the SD model in predicting the chemical waste generated in the upcoming decade. By utilizing system dynamics, the model aims to alleviate the problem of excessive accumulation of chemical waste, whether in solid or liquid form, by reducing costs and achieving optimal efficiency throughout the disposal process. Since chemical waste is highly toxic, utmost precautions must be taken during storage and transportation before disposal.

This study demonstrates that the developed system dynamics model considers multiple factors influencing waste volumes, such as departure and arrival rates. By capturing the dynamic relationships between these factors and waste generation, the model provides valuable insights into the potential changes in the total amount of waste a hospital generates. The results indicate an increase in chemical waste generation over the forecast period of 10 years, reaching 2701.89 kg by 2031. A 50-year forecast shows that the projected waste volume is 4552.39 kg.

In the year of the study (2021), the total amount of waste generated by the University of Jordan Hospital was recorded as 2371.5 kg, with liquid waste (Formalin) accounting for 1904.05 kg and solid waste amounting to 467.45 kg. While the quantity of chemical waste generated may not be enormous, the critical issue lies in its highly hazardous nature, necessitating specific storage and disposal procedures to ensure the safety of both staff and patients. A system dynamics model allows for a comprehensive understanding of the underlying dynamics and interdependencies in healthcare chemical waste generation, facilitating effective waste management strategies.

With an amplification factor of 10, the model's forecasted rate shifts from 0.4 to 0.47 within a decade. This dynamic demonstrates the impact of various variables on generation rates, emphasizing the importance of considering multiple factors to understand observed trends.

A concerning trend in terms of increasing chemical waste is expected according to the predicted results of the model. Over a decade, the growth rate is 14%, rising to 30% over two decades and 48% in the following ten years. The proportion then jumps to 68% after 40 years, representing an astounding 92% growth over a half-century. These estimates highlight the critical importance of implementing rapid and efficient waste management methods.

The model's ability to target departments with the largest chemical waste generation adds significance to the study, increasing its prediction capability and improving its importance in developing long-term waste management plans. The study emphasizes the necessity of establishing effective strategies for tackling the adverse effects of chemical waste on human health and the environment in light of growing waste rates. By combining predictive skills with practical insights, this research is a critical tool in solving the urgent concerns resulting from increasing chemical waste, eventually preserving the safety of both people and the ecosystem.

Acknowledgments

We want to express our sincere thanks to the ***Deanship of Scientific Research at The University of Jordan*** for Funding this work (Project #195 Grant #2572 Decision #176/2022-2023 Date 22 June 2023).

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Appendix: Equations and Rates Implemented in Vensim

Model Mathematical Equations

Patient Population

$P_t = P_{t-1} + (Arrivals - Departure)$

$Arrivals = Ƥ \times \Gamma_A$

$Departures = Ƥ \times \Gamma_D$

The mean amount of waste for each floor (kg/day):

$$\bar{\mu} = \frac{\sum \boldsymbol{X}}{\boldsymbol{N}}$$

Rate of waste generation for each floor (Kg/bed/day):

$$\boldsymbol{\Gamma_p} = \frac{\bar{\mu}}{\sum \boldsymbol{p}}$$

The percentage of change (%$\boldsymbol{\Delta}$

$$\%\boldsymbol{\Delta} = \frac{\boldsymbol{V_N} - \boldsymbol{V_O}}{\boldsymbol{V_O}} * \mathbf{100}\%$$

Accelerated rate of change

$$\boldsymbol{\alpha} = (\%\boldsymbol{\Delta_N} - \%\boldsymbol{\Delta_O}) \times \boldsymbol{\lambda}$$

Software Related Equations and Rates

(01) UG_C-S / Y=
$\boldsymbol{p}$V* UG_C-S **Γ**
Units: kg

(02) UG_C-S **Γ=**
6.3864e-05
Units: kg/person

(03) UG_C-S=
UG-S / Y
Units: kg

(04) $2G_H$-S / Y=
$\boldsymbol{p}$V*2G-S **Γ**
Units: kg

(05) $2G_H$-S **Γ**=
3.52181e-05
Units: kg/person

(06) $2G_H$-S=
$2G_H$-S / Y
Units: kg

(07) $3G_C$-F / Y=
$\boldsymbol{p}$V*$3G_C$-F **Γ**
Units: kg

(08) $3G_C$-F **Γ**=
0.00044319
Units: kg/person

(09) $3G_C$-F=

$3G_C$-F / Y
Units: kg

(10) $3\ G_C$-S / Y=
pV*$3\ G_C$-S **Γ**
Units: kg

(11) $3\ G_C$-S **Γ**=
0.000413687
Units: kg/person

(12) $3\ G_C$-S=
$3\ G_C$-S / Y
Units: kg

(13) $3\ G_H$-S / Y=
pV*$3\ G_H$-S **Γ**
Units: kg

(14) $3\ G_H$-S **Γ**=
6.42926e-06
Units: kg/person

(15) $3\ G_H$-S=
$3\ G_H$-S / Y
Units: kg

(16) $4G_H$ **Γ**=
3.76469e-05
Units: kg/person

(17) $4G_H$-S / Y=
pV*$4G_H$ **Γ**
Units: kg

(18) $6G_H$-S / Y=
pV*$6G_H$-S **Γ**
Units: kg

(19) $8G_H$-S / Y=
pV*$8G_H$-S **Γ**
Units: kg

(20) $4G_H$-S=
$4G_H$-S / Y
Units: kg

(21) $6G_H$-S **Γ**=
8.97953e-05
Units: kg/person

(22) $6G_H$-S=
$6G_H$-S / Y
Units: kg

(23) $8G_H$-S **Γ**=
2.14309e-06
Units: kg/person

(24) $8G_H$-S=
$8G_H$-S / Y
Units: kg

(25) *A*=*A* **Γ***P_P
Units: person

(26) *A* **Γ**=
0.016628
Units: Dmnl

(27) -Chemical waste=
Tissue G_H-S/ Y+3G_C-F / Y+ER_C F / Y+3G_C-S / Y+ UG-S / Y+2G-S / Y+4G_H-S / Y+6G_H-S / Y
+Gynecology $_H$ S / Y+wings $_H$ S / Y+MICU $_H$ S / Y +8 G_H-S / Y+3G_H-S / Y
Units: kg

(28) *∂*= *∂* **Γ*** P_P
Units: person

(29) *∂* **Γ**=
0.0035
Units: Dmnl

(30) ER_C F / Y=
pV*ER F-C **Γ**
Units: kg

(31) ER_C F=
ER-C F / Y
Units: kg

(32) ER_C F **Γ**=
2.67171e-05
Units: kg/person

(33) FINAL TIME = 30
Units: Year
The final time for the simulation.

(34) Gynecology $_H$ S=
Gynecology $_H$ S / Y
Units: kg

(35) Gynecology $_H$ S / Y=
Gynecology $_H$ S **Γ*****p***V
Units: kg

(36) Gynecology $_H$ S **Γ**=
3.71468e-06
Units: kg/person

(37) INITIAL TIME = 0

Units: Year
The initial time for the simulation.

(38) $MICU_H$ S=
MICU $_H$ S / Y
Units: kg

(39) MICU $_H$ S / Y=
$MICU_H$S **Γ*** ***p***V
Units: kg

(40) MICU $_H$ S **Γ**=
9.50102e-06
Units: kg/person

(41) ***p***V=
$p_{\mathcal{P}}$ *0.0679539
Units: person

(42) $p_{\mathcal{P}}$ = INTEG (-∂, 1.03e+07)
Units: person

(43) SAVEPER =
TIME STEP
Units: Year
The frequency with which output is stored.

(44) TIME STEP = 1
Units: Year
The time step for the simulation.

(45) tissue G_C F **Γ**=
0.00225046
Units: kg/person

(46) tissue G_H-S / Y=
pV*tissue-C F **Γ**
Units: kg

(47) tissues-G_C F=
tissue G_H-S / Y
Units: kg

(48) wings $_H$ S=
wings H S / Y
Units: kg

(49) wings $_H$ S / Y=
pV*wings $_H$ S **Γ**
Units: kg

(50) wings $_H$ S **Γ**=
5.85777e-06
Units: kg/person

Ground/Floor	G
Formalin	F
Patient volume	p_V
Rate	**Γ**
Clinics	C
Hospital	H
Patients Population	$p_{\mathcal{P}}$
Arrival	A
departure	∂
Solid	S
Per year	/Y
Underground	U