SWIMS: a dynamic life cycle-based optimisation and decision support tool for solid waste management

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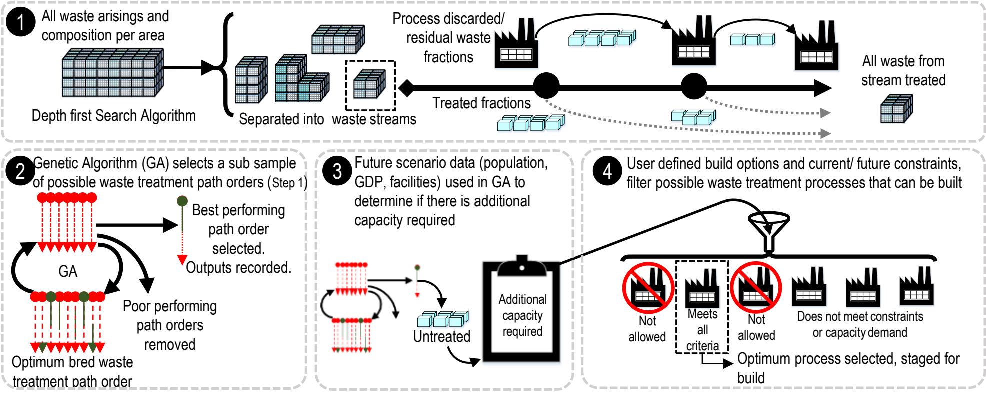
Abstract

Solid waste management (SWM) decision makers are under increasing pressure to implement strategies that are both cost effective and environmentally sound. Consequently, SWM has developed into a highly complex systemic planning problem and analytical tools are needed to assist in the development of more sustainable SWM strategies. Here, we present the Solid Waste Infrastructure Modelling System (SWIMS) software, which is the first non-linear dynamic, LCA-based optimisation tool for SWM that optimises for both economic and environmental performance. The environmental and economic costs of treating generated wastes at available treatment facilities are calculated through a series of life cycle process models, based on non-linear expressions defined for each waste material and each treatment process type. Possible treatment paths for waste streams are identified using a depth first search algorithm and a sequential evolutionary genetic algorithm is used to prioritise the order of these paths, in lieu of user defined optimisation criteria and constraints. SWIMS calculates waste arisings into the future and determines if it is possible to treat generated waste, while considering present and future constraints (e.g. capacity). If additional capacity is required, SWIMS will identify the optimum infrastructure solution to meet this capacity demand. A demonstrative case study of MSW management in GB from 2010 to 2050 is presented. Results suggest that sufficient capacity is available in existing and planned infrastructure to cope with future demand for SWM and meet national regulatory and legislative requirements with relatively little capital investment beyond 2020. SWIMS can be used to provide valuable information for SWM decision makers, particularly when used to analyse the effects of possible future national or regional policies.

Graphical abstract



Key Words

Life cycle assessment, optimisation, infrastructure planning, waste management, non-linear programming, sustainability

Abbreviations

BAU	Business as Usual
BTS	Baseline Timestep
DFSA	Depth First Search Algorithm
FTS	Final Time Step
GA	Genetic Algorithm
GB	Great Britain
GHG	Green House Gas
GOR	Government Office Region
GVA	Gross Value Added
GWP	Global Warming Potential
HWRC	Household Waste Recycling Centre
ITRC	Infrastructure Transitions Research Consortium

LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
MSW	Municipal Solid Waste
NISMOD1	National Infrastructure Systems Model 1
SMART	Solid Waste Management Resource Recovery Tool
SI	Supplementary information
SWIMS	Solid Waste Infrastructure Modelling System
SWM	Solid Waste Management
SWOLF	Solid Waste Optimisation Life-cycle Framework
TF	Treatment Facility
TP	Treatment Plant
WTP	Waste Treatment Path

1. Introduction

The quantity and complexity of waste generated globally is expected to increase significantly in the coming decades as a result of population growth, socioeconomic development and rapid urbanisation (Hoornweg and Bhada-Tata, 2012). This makes solid waste management (SWM) a challenging task for decision-makers, who are required to provide essential waste collection and disposal services, often under increasingly stringent budgetary pressures and regulatory requirements. Ineffective SWM can incur high costs and have detrimental effects on the environment. For example, the sector is estimated to produce 3% of global greenhouse gas (GHG) emissions, primarily the result of methane emissions from landfill (Fischedick *et al.*, 2014). However, effective SWM can reduce costs and recover valuable materials and energy. Hence, policy makers are increasingly looking to the SWM sector to improve its environmental performance and play a major role in society's drive towards improved resource efficiency.

Decision makers are expected to design and implement SWM systems that are both cost effective and environmentally sound, and contribute to wider societal goals such as renewable energy recovery and the preservation of natural resources (Giugliano *et al.*, 2011). Accordingly, SWM systems have become increasingly complex, encompassing numerous multi-functional technologies designed to manage specific waste streams. Furthermore, as the characteristics of waste arisings are often highly variable between regions, unique strategies must be developed to manage SWM in each region (Bisinella *et al.*, 2017). Regional decision makers are therefore faced with a multifaceted systemic planning problem, involving consideration of (amongst others) waste collection scheme design, waste treatment technology selection, site selection, estimation of capacity needs (involving the prediction of future waste arisings and composition), and transportation scheduling and planning. With such complex demands there is a need for analytical tools that can assist in developing long- and short-term SWM strategies with respect to various sustainability objectives (Qian *et al.*, 2011). Furthermore, such tools must enable consideration of SWM systems as a whole, because they are complex and inter-dependent, with activities in one region often affecting management practices in another (Cobo *et al.*, 2017)

In recent decades, a range of integrative systems analysis techniques have been applied to SWM systems to provide interdisciplinary support for policy- and decision-making. (for a thorough, critical review, see Chang *et al.* (2011) and the updated review of Tan *et al.* (2014)). Briefly, the available techniques can be classified into two domains: a) system assessment tools, which include material flow analysis, risk assessment, environmental impact assessment, socio-economic assessment, and life cycle assessment (LCA); and b) systems engineering models, which include cost-benefit analysis, forecast modelling, simulation modelling, and optimisation modelling.

Life cycle assessment (LCA) is a well-established system assessment tool that has been extensively applied to support environmentally-sound SWM decision making. For example, Turner *et al.* (2016) used LCA in combination with material flow analysis to evaluate the existing SWM system in Cardiff, Wales and compared it with alternative, hypothetical systems to explore the potential impacts of different national policy measures. The environmental performance of the SWM system in the Lombardia region of Italy was assessed using LCA by Rigamonti *et al.* (2013), who then investigated how performance could be improved in the future through scenario analysis. LCA has also been used to evaluate and compare waste collection systems (e.g. Gilardino *et al.* (2017)) and waste treatment processes for different waste streams, such as supermarket food waste (Brancoli *et al.*, 2017), street sweepings (Bartolozzi *et al.*, 2018), source-segregated recyclable materials (Turner *et al.*, 2015), construction and demolition waste (Borghi *et al.*, 2018), and plastic waste (Arena *et al.*, 2015). Over the past two decades, a range of LCA software tools has been developed specifically to analyse SWM processes and systems. The most sophisticated of these is EASETECH, which was developed at the Technical University of Denmark (Clavreul *et al.*, 2014). EASETECH comprises a highly user-friendly interface that allows users to model the heterogeneous flows of waste between treatment processes in a SWM system and evaluate the potential environmental impacts of the modelled system. However, while EASETECH and LCA of SWM in general are useful for assessing the environmental performance of waste treatment processes and systems, the detailed modelling and optimisation of the combined environmental and socioeconomic performance of these processes and systems has received rather less attention (Chang *et al.*, 2011; Tan *et al.*, 2014).

Unlike system assessment tools such as LCA, which focus on the assessment of existing, past or hypothetical systems, systems engineering models emphasise the design and optimisation of a system according to one or multiple specific objective function(s) and with respect to any constraints placed on that system (Juul *et al.*, 2013). Optimisation for SWM presents an opportunity to maximise resource and energy recovery from waste, enhance environmental sustainability, and simultaneously minimise financial costs. A number of optimisation models have been developed to analyse SWM systems (for an overview, see Tan *et al.* (2014)), but only a few support combined economic and environmental optimisation (e.g. Chang *et al.* (2012)). One such model is SMART (the Solid Waste Management Resource Recovery Tool), a multi-period optimisation model for SWM based on mixed-integer linear programming (Tan *et al.*, 2014). SMART includes a sophisticated financial costing model based on net present value calculations (excluding discounting). However, only four different waste treatment technologies are considered in the model (landfill, incineration, composting, and recycling), which are modelled on best available technology only (i.e. “average” technologies of today are not considered). The model is also simplified in several other aspects: only seven different waste types are included (food, yard, paper, plastics, glass and ceramic, metal, and textile wastes), which does not reflect the complex nature of waste composition; transportation and transfer costs are not considered; potential climate impacts are calculated as technology-specific and are not related to waste type/composition.

SMART, along with many other combined economic-environmental optimisation models, is primarily designed for cost modelling. To improve the modelling of environmental impacts, researchers have recently developed optimisation models based on the LCA framework. For example, the Solid Waste Optimisation Life-cycle Framework (SWOLF), developed at North Carolina State University, is a sophisticated dynamic optimisation tool for the integrated analysis of SWM systems based on multi-stage linear programming (Levis *et al*., 2013) that enables the development of integrated SWM strategies which consider existing as well as (possible) future infrastructure. OptiWaste is a LCA-based SWM optimisation model based on linear programming that enables optimisation for multiple criteria using weighting factors (Münster *et al.*, 2015). Two models based on linear programming (single and multi-objective) and the integrated use of LCA data were developed and applied by Tascione *et al.* (2016) to optimise the environmental performance of waste management systems in the Abruzzo region, Italy. These tools demonstrate that it is feasible and potentially valuable to decision makers to develop optimisation models based on the LCA framework.

A common feature of LCA-based optimisation models for SWM is the use of linear programming techniques. Models are generally based on a simplified mass flow modelling approach, which considers only flows of waste streams, such as residual waste, rather than waste materials (i.e. the component materials of a waste stream). Models therefore do not address the unique response of each waste material type to a given processing method, and cannot account for regional and temporal variations, or post-treatment changes in waste stream composition, which may strongly affect the economic and environmental performance of the SWM system (Hoornweg and Bhada-Tata, 2012). SWOLF uses linear expressions to account for mass flows while OptiWaste is based on a simplified network flow model that does not include multi-output processes (i.e. processes that accept one waste stream and output multiple other waste streams). While such functionality is afforded to users of the waste-LCA tool EASETECH in assessing the environmental performance of SWM technologies, it has not to date been considered in optimisation models for SWM, because of the difficulty of solving this non-linear optimisation problem (Levis *et al.*, 2013). To account for the heterogeneous, changeable and varied nature of waste streams, a non-linear programming approach is required. Therefore, there is a need for algorithms to efficiently solve non-linear optimisation problems for large-scale SWM systems models (Kumar *et al.*, 2010).

This paper presents the Solid Waste Infrastructure Modelling System (SWIMS) software, which is the first dynamic, non-linear, life cycle-based optimisation tool for SWM that optimises for both economic and environmental performance. This is a major benefit as SWIMS is able to optimise and plan waste treatment for multiple criteria and evolve a highly effective solution. The functionalities of SWIMS expand on those of previously developed linear LCA-based SWM models (described above). Whilst these models function well in modelling simplified SWM systems, such as those containing few process types or waste streams (with non-changeable compositions), they struggle to simulate the flows and processing of complex, changeable and varied wastes, particularly at large spatial scales (e.g. at the regional or national scale) where numerous bespoke processing methods are used. SWIMS is intended to be used to support decisions concerning both environmental and economic impacts within the development of sustainable waste management infrastructure. It can be used to help inform and incorporate the European Union’s circular economy package into SWM strategy making and assist policy makers to meet the sustainable development goals adopted by the United Nations (Murray *et al.*, 2017). The purpose of this paper is to describe the modelling framework of the SWIMS software (Section 2) and, through a real-world case study, demonstrate its functionalities (Section 3). Concluding remarks, including an overview of the model’s limitations and areas for further development, are then described in Section 4.

2. Methodology

SWIMS is a dynamic, non-linear, life-cycle based environmental and financial optimisation tool for SWM. The approach and software have been developed for application in Great Britain (GB) but are generalised, enabling potential application to other countries and at different spatial scales. The following sections describe the four main parts of SWIMS: Waste Treatment Paths (WTP), waste path optimisation, additional capacity calculations and the infrastructure builder.

It is important to understand that many of the processes described below occur within the model concurrently, even though they are described sequentially for clarity of communication. Hence, the descriptions for certain processes may refer to processes that have not yet been introduced.

2.1 Overview of modelling framework

A schematic view of the modelling framework is presented in Figure 1. Details of each step are given in the subsequent sections. The dynamic, bi-level optimisation problem of waste management can be summarised as follows:

Step 1. Waste generation

This initial step requires the determination of the total mass of waste produced and its composition. Total waste produced is calculated using regional socioeconomic and demographic data. Waste composition, comprising up to 25 different materials, is defined by producer type.

Step 2. Waste collection

The behaviours of different waste producer types are captured in sets of disposal rules that determine the allocation of waste materials, including contaminants, to different waste collection processes. The blend of waste materials disposed to each different collection process is labelled as belonging to the appropriate waste stream and is transported to primary waste treatment facilities as waste flows, containing specific masses of waste material.

Step 3. Waste management pathfinder

A depth first search algorithm (DFSA) determines the possible treatment paths that waste flows can take through the network of treatment facilities (TF) (Tarjan, 1972). A genetic algorithm (GA) is then used to prioritise the order of these paths for the collection and transport of waste flows to treatment facilities until all waste is treated. The optimal WTP for the waste flows to facilities is selected with reference to user defined optimisation criteria and constraints. This is essential due to the finite capacity of each facility which makes optimisation much more difficult. Strategies define and restrict the space in which SWIMS can utilise areas, transport, and groups of waste treatment facilities. The space refers to a series of compounding constraints and rules, e.g. restrictions on types of TF, restrictions on exports to external areas, and rules governing which waste type can be sent to a TF.

Step 4. Waste treatment

Waste is treated within facilities, such that the materials are treated, rejected, or treated with by-products (or a combination of all three). If treated, the material is removed from the system. If rejected, the material enters another waste flow and is sent for further treatment. If a by-product fraction is produced, the treated fraction is removed and the residual fraction enters a new waste flow for further treatment.

Step 5. Future infrastructure planner

The SWIMS infrastructure planner takes into account future waste arisings and composition within defined planning horizons. The lifespan and absolute capacity of a waste TF is considered and the planner determines whether there is sufficient capacity to manage the total waste produced, within the user defined constraints. If insufficient capacity is predicted, a genetic algorithm determines whether the current facilities require upgrading, or whether new infrastructure is needed to meet or exceed a set capacity margin.

Step 6. Infrastructure builder

User defined strategies determine which TFs can be built. If the TF suggested within the infrastructure finder step is permitted within the strategy, the TF is planned and staged for addition. However, if it does not, the TF is rejected.

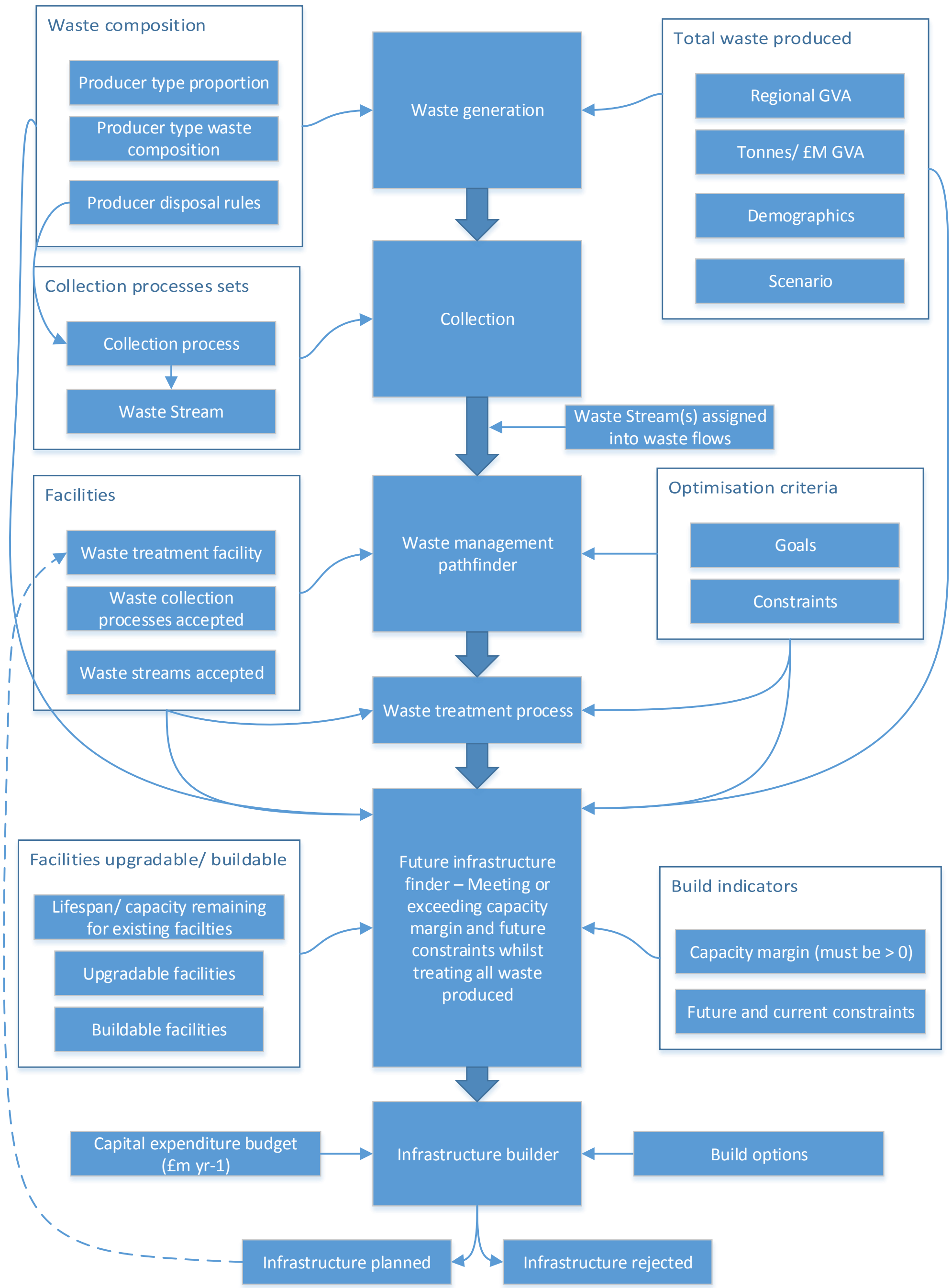


Figure 1. A simplified linear flow diagram of the main process steps within SWIMS, with the primary grouped processes for each main step shown. The secondary processes between the steps and the user defined inputs are not shown.

2.2 Assumptions

The units of time in which waste is produced, collected and managed, and for which infrastructure planning is carried out, are called timesteps. A timestep can be any duration of 'real-world' time, such as a year, month, week or day. The base case (or initial) timestep is:

$$t = BTS + (n - 1) \tag{1}$$

Where *BTS* is the baseline timestep (e.g. 2010), *n* is the number of timesteps.

Following this, optimal waste management is planned for the next *T* years ($n = 1\ldots N$). The number of timesteps can be defined as follows:

$$n = 1,2,\ldots,N \tag{2}$$

Where *n* is the nth timestep, and *N* represents the total number of timesteps for which the model is run. Note that the planning frequency (i.e. how often the model plans new infrastructure) and planning horizon (how far into the future the model plans for) are defined by the user.

Optimisation is performed with one or multiple objectives (e.g. minimise total costs and/or maximise energy recovery) and constraints (e.g. send less than 10% of waste to landfill by 2019). More details on the optimisation method are provided below.

Input data must be set to the duration of a timestep, e.g. the rate at which amounts of waste are generated during a timestep. SWIMS has many input data tables which require per timestep data, hence running SWIMS with a higher temporal resolution will require more input data and increase the set-up time. A fundamental constraint of the model is that all waste produced in a timestep is treated within the same timestep, with any waste that cannot be treated due to a shortage of capacity classified as untreated waste which is not carried forward to the following timestep.

The length of time that it takes a computer to process a timestep will be roughly constant regardless of the length of real-world time that each timestep represents. For this reason, and taking account of the data input overhead, a maximum timestep duration of one year is recommended, which gives a sufficiently granular temporal resolution in most cases.

In some instances, precise and accurate input data will not be available and modelling assumptions will be required. Suitable assumptions are addressed in the following sections. Despite this, it should be emphasised that the proposed optimisation model for waste management is versatile and can easily be adapted to incorporate more refined information as it becomes available.

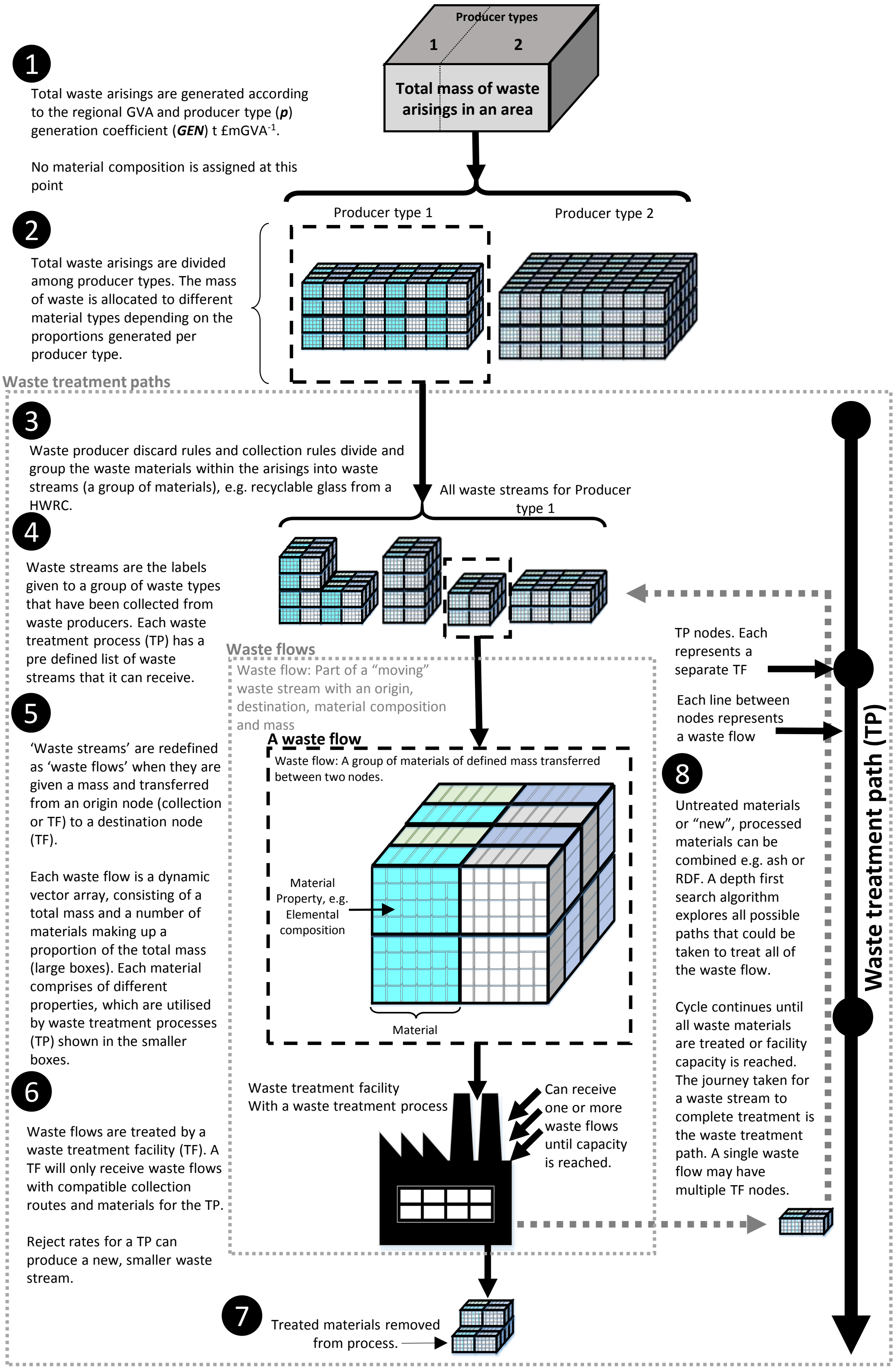
2.3 Waste flow modelling in SWIMS

The representation of waste flows through the system is based on a network mass flow model. The network is built up of nodes, which represent the waste treatment facilities that populate the system. The model accounts for all incoming and outgoing mass flows of waste between the nodes that make up the network, with waste entering the system through processes that collect waste from waste producers (more information below). Figure 2 describes schematically the processes occurring within the running of the model.

Flows of waste are modelled heterogeneously, i.e. they may contain one or multiple waste materials. A waste stream is a specific category of waste (e.g. residual waste or textile waste) and is initially defined by how it is collected, e.g. from kerbside bins or specialist bins at a household waste recycling centre (HWRC). A specific mass of waste, including both target materials and contaminants, collected by a waste collection process in a given area and timestep forms a waste flow. Waste flows have a total mass equal to the sum of the masses of the constituent waste materials.

Waste materials have a type, mass (within a given waste flow) and specific set of physico-chemical properties. While material type is persistent, the specific properties associated with a material are dynamic and may be modified by certain types of waste treatment processing. Nevertheless, regardless of any changes to a waste's properties it will always be traceable to the original material type. This enables the fate of each single material type to be tracked from waste generation to treatment and disposal. The benefit of this approach is that it allows SWIMS to identify the optimal treatment paths for different waste flows based on the physico-chemical properties of the waste materials contained with those flows. For example, two flows from the same waste stream may have different optimal treatment paths if, despite being the same waste stream type, differing masses within the flow or geographic location resulted in differing facilities and path orders being available, changing the physico-chemical properties at the TFs.

Different waste collection processes and treatment processes are significantly influenced by a waste producer's "willingness" to participate in recycling, composting, etc. within SWIMS. The producer's behaviour affects the level of contamination in a waste flow; this is likely to change spatially, temporally and demographically. As the waste flows are modelled heterogeneously, and with distinct and dynamic compositions, ratio constraints based on non-linear expressions are required for each waste material and each treatment process. This introduces non-linear constraints, greatly increasing the complexity of the model, and results in what is suspected to be an NP-hard decision problem (see Kellerer *et al.* (2004)). The problem is addressed in SWIMS through a non-linear optimisation algorithm, as described below.



Producer types
1
2
Total mass of waste arisings in an area
1
Total waste arisings are generated according to the regional GVA and producer type (p) generation coefficient (GEN) t £mGVA-1.
No material composition is assigned at this point
Producer type 1
Producer type 2
2
Total waste arisings are divided among producer types. The mass of waste is allocated to different material types depending on the proportions generated per producer type.
Waste treatment paths
3
Waste producer discard rules and collection rules divide and group the waste materials within the arisings into waste streams (a group of materials), e.g. recyclable glass from a HWRC.
All waste streams for Producer type 1
4
Waste streams are the labels given to a group of waste types that have been collected from waste producers. Each waste treatment process (TP) has a pre defined list of waste streams that it can receive.
Waste flows
Waste flow: Part of a "moving" waste stream with an origin, destination, material composition and mass
A waste flow
Waste flow: A group of materials of defined mass transferred between two nodes.
TP nodes. Each represents a separate TF
Each line between nodes represents a waste flow
Waste treatment path (TP)
5
'Waste streams' are redefined as 'waste flows' when they are given a mass and transferred from an origin node (collection or TF) to a destination node (TF).
Each waste flow is a dynamic vector array, consisting of a total mass and a number of materials making up a proportion of the total mass (large boxes). Each material comprises of different properties, which are utilised by waste treatment processes (TP) shown in the smaller boxes.
Material Property, e.g. Elemental composition
Material
8
Untreated materials or "new", processed materials can be combined e.g. ash or RDF. A depth first search algorithm explores all possible paths that could be taken to treat all of the waste flow.
Cycle continues until all waste materials are treated or facility capacity is reached. The journey taken for a waste stream to complete treatment is the waste treatment path. A single waste flow may have multiple TF nodes.
6
Waste flows are treated by a waste treatment facility (TF). A TF will only receive waste flows with compatible collection routes and materials for the TP.
Reject rates for a TP can produce a new, smaller waste stream.
Waste treatment facility
With a waste treatment process
Can receive one or more waste flows until capacity is reached.
7
Treated materials removed from process.

323

Figure 2. Visualisation of the steps taken to generate waste flows, utilise existing TP and initialise new TP. A TP consists of the processes used for a waste stream to be collected, transported and treated.

2.4 Waste generation

Waste producers are the agents within the system that generate and dispose of waste. The material composition of generated waste is predetermined for each producer type within the database. An example of material generation is shown in Figure 2. Each geographic region's initial waste production is defined as primary waste, with reprocessed wastes sent for further treatment defined as secondary waste. One or more waste producer types (e.g. urban household or rural household) may be defined for each geographic area represented within the system. Waste arisings *w* (tonnes) for producer type *x* in area *a* at timestep *t* are:

$$w_{x,a,t} = GVA_{x,a,t} \cdot GEN_{x,a,t}$$

$$GVA_{x,a,t} = P_{x,a,t} \, . TotalGVA_{a,t}$$

$$GEN_{x,a,t} = \; GEN_{x,a} \cdot (1 - d_x)^t$$

$$t = 0, 1 \dots FTS \tag{4}$$

where $GVA_{x,a,t}$ is gross value added (£ million) for producer type *x* in area *a* at timestep *t*; $P_{x,a,t}$ is the proportion of producer type *x* in the population of area *a* at timestep *t*, $GEN_{x,a,t}$ is the waste generation rate (tonnes/£M GVA[1]) for producer type x, in area a for timestep t, d_x is a "decoupling" rate constant (see below) for producer type x, and FTS is the final timestep.

Based on the above, total waste arisings, W, *in* area a at timestep t are:

$$W_{a,t} = \sum w_{x,a,t} \tag{5}$$

Temporal changes in waste arisings are modelled in SWIMS by assuming a positive correlation between waste generation and economic activity (i.e. GVA). Historical trends in most industrial economies show a link between resource use (and resultant waste generation) and economic activity (Hoornweg and Bhada-Tata, 2012). It has, however, been demonstrated that more efficient use of resources can break the link between resource use and economic growth (Bithas and Kalimeris, 2018) Hence, decoupling refers to the concept of de-linking resource use from economic growth over time, i.e. the generation of less waste per unit of economic activity. Mazzanti *et al.* (2012) show that a general trend towards decoupling of economic growth and waste arisings is occurring in the European Union. For this reason, SWIMS allows a waste decoupling factor to be applied. A waste decoupling factor can also be applied to prevent an exponential growth in waste generation. The pre-set values within SWIMS range from 0 to 4% per annum determined from historical projections and calculations as reported by Hall *et al.* (2016b), but can be redefined by the user.

[1] GVA reported here is the measure of the increase in the value of the economy due to the production of goods and services at a regional level.

2.5 Waste collection

2.5.1 Waste collection processes

Waste collection processes represent the way in which waste enters the waste management system and are the point at which groups of waste materials are combined into waste streams. Waste collection processes should be thought of as the types of ‘bins’ available to waste producers. Each waste collection process produces a single waste stream and different waste collection processes may produce the same waste stream. For example, a “residual” waste stream may be produced by a “household kerbside collection, residual waste” collection process as well as a “household waste recycling centre, residual waste” collection process.

Waste collection processes do not exist in isolation but are always part of a coherent group available to waste producers, here called a “waste collection process set”. Waste collection process sets are defined because there are certain processes that do not logically belong in the same set. For example, there are several types of kerbside collection process for recyclable materials, which can be categorised as single-stream co-mingled (all recyclable waste mixed together in one bin), two-stream co-mingled (most recyclable waste mixed together in one bin with something separate, such as glass) and sorted/source segregated (where specific types of recyclable waste materials are separated by the waste producer and placed in their own exclusive bin). In practice, no one waste producer (e.g. a householder) would be offered more than one of these types of kerbside recycling collection, hence they should not belong to the same waste collection process set. However, a waste collection process set should be made up of a diverse range of processes to collect a variety of waste types: e.g. from the kerbside, at HWRC, bring banks and public street bins.

For each geographic area *a*, the proportion of the population that is served by each waste collection process set is pre-determined within the database. Each material type has a proportion that is collected by a single waste collection process type. The material collected by each waste collection process type creates a unique waste stream (up to 85) as shown in Figure 2.

The timestep-based approach allows for the simulation of changes in collection service provision over time, for example, to replicate the increased provision of source-segregated food waste collection services in the UK since 2010.

Waste collection metrics are calculated from coefficients with set transport distances on a t km^{-1} basis, details of which are given within the Supplementary Information (SI).

2.5.2 Waste producer discard rules

Waste discard rules are used to define, for each waste producer type, the proportion of each generated waste material discarded to each waste collection process they are offered. Also defined for each waste collection process is a) a contamination rate, i.e. the proportion of the waste materials in that waste collection process that are non-target materials; and b) the collection process to which the contaminant material should be assigned. Contamination rates are predefined for each material and waste producer type as a fraction of the waste collected based on user inputs and literature values (Clavreul *et al.*, 2014), which is then redirected to a residual TF upon receipt at the initial TF. For example, a paper recycling collection process has 10% contaminants and the contaminants belong to the residual collection process. Residual waste can be a source of contamination for a recyclable materials collection process. However, the general residual waste collection process, by nature of being a residual waste collection process, cannot contain contaminants.

As waste composition and waste discard rules are defined for each specific waste producer type it is possible to simulate changes in waste producer behaviour by varying the proportion of different waste producer types over time. For example, good waste producer behaviour would involve the discarding of “target” materials (e.g. recyclables and food waste) into the separate bins (i.e. collection processes) with minimal contamination, thus diverting the valuable materials at the source from the residual waste stream. Bad behaviour would involve the opposite. Hence, by populating the system at $t = 0$ with a high proportion of poorer behaving waste producer types and then increasing the proportion of well-behaved producer types in later timesteps, an improvement in waste producer behaviour may be simulated.

2.6 Waste treatment

All waste collected by each waste collection process in an area for a given timestep forms a waste flow, which is identified as being of a specific waste stream type and is directed for treatment accordingly. Given their different material compositions and resulting physico-chemical properties, different waste streams require different types of treatment. There are 168 discrete waste treatment processes currently built into the database, covering a wide range of technologies (e.g. landfill, composting, anaerobic digestion, reprocessing, etc.), each of which has a variety of configurations. For each waste stream, the type(s) of waste treatment technology that can be used to treat that waste stream is defined by the user. This prevents, for example, “residual waste” from being treated via paper reprocessing.

In SWIMS, waste handling sites are waste TFs. Each geographic area represented within the system is initially ($t = 0$) populated by a number of TFs. Facilities that are due to become operational in the future ($t \geq 1$) may also be specified by the user; these are then added to the network when appropriate. These TFs represent the nodes of the network flow model. TFs are defined by a name, location (geographic area), technology type (e.g. in-vessel composting or landfill, sanitary), operating capacity (tonnes per year), theoretical maximum capacity (tonnes per year), the timestep in which they became/will become operational, and the capital cost (£ million) of their construction. The standard of the technology type can also be specified e.g. “average technology”, “best available technology”.

A system may comprise several hundred discrete TFs (for example, the system of the case study described below initially comprise 904 facilities, with a further 1546 added to the system by 2020) and cover a wide array of technologies. Hence, to simplify the modelling of waste treatment, each technology type is categorised into one of 14 different waste treatment process models. Process models may be single- or multi-stage. At its most basic, a process model may involve the transfer of a waste flow, without any modification to its material properties, from one TF to another (e.g. a transfer station). Other process models are more complex, multi-stage operations entailing several different processing steps. For example, waste treatment at a TF of technology type “mechanical biological treatment with in-vessel composting [average technology]” is modelled using the multi-stage “mechanical biological treatment” process model, as follows: Step 1) *initial sort* in which a proportion of each input material type is “rejected”, i.e. transferred to a residual waste stream; Step 2) *physical separation* where a proportion of each input material type is transferred into different waste streams (e.g. fines, for biological treatment internally; residual waste, for treatment/disposal elsewhere; or recyclables, for reprocessing elsewhere), with each output waste stream also containing a proportion of contamination. Step 3, *Biological treatment* where materials that are accepted for biological treatment during Step 2 are transferred to a “composting” or “anaerobic digestion” process model. Here, the physico-chemical properties of input materials are changed based on the parameters of the biological treatment process (in this case, in-vessel composting) such that the properties of the output are different from those of the input.

2.7 Capacity

At the start of the model all existing and planned/under construction TFs have a defined annual maximum operating capacity that cannot be exceeded. Facilities can be upgraded to extend their lifespan and potentially their capacity, except for landfills, which have both a maximum annual operating capacity and a finite capacity. The landfill-specific cumulative capacity constraint prohibits the model from disposing of more waste than an individual landfill can hold. Once the total capacity is reached, the landfill is removed from operational use and becomes a legacy landfill in the model.

2.8 Genetic algorithm and optimisation of WTPs

All possible waste treatment paths (i.e. chains of waste treatment processes) that accord with the constraints (database and user defined) exist at the start of a model run. As SWIMS assesses the performance of these paths rather than individual waste treatment processes, all possible paths must be tested to guarantee that an optimal solution is selected. However, the variety of waste producer types (and associated discard rules), waste streams, waste treatment processes, geographic areas and government and user-defined constraints that may be modelled means there are too many permutations to test within a reasonable run time. SWIMS uses a path order optimiser, which due to the capacity constraints of TF makes this problem difficult to solve, similar to the 'bin packing' or 'travelling salesman' optimisation problems (Larrañaga *et al.*, 1999).

To address this, a DFSA is used for each waste flow. Each path has implications for the utilization of the capacity of different waste treatment facilities. Using one path to process a mass of waste reduces the capacity available to other waste flows. If any facility on a path has no remaining capacity, the entire path becomes unavailable. Therefore, the order in which the WTPs are used is very important to the performance of the system as a whole. Finding the ideal order is non-trivial. Paths that, in isolation, look very good may result in the use of very bad paths to process a larger quantity of waste further down the line. Therefore, finding the best order of use is crucial to optimizing the performance of the system as a whole. A sequential evolutionary genetic algorithm (GA) is employed to determine the optimum order of paths for a waste stream so that the available capacity of the various treatment facilities is best utilized to achieve the optimisation goals (Mayer *et al.*, 1999). A GA is used because of its record in finding optimal or near-optimal solutions quickly and its computational efficiency (Kumar *et al.*, 2010).

As shown in Figure 3, the GA populates a model run with an initial random selection of WTPs, referred to as "parents". The performance of these parents is assessed according to the optimisation criteria and user selected optimisation criteria weights. One or more of the following eleven optimisation criteria may be selected:

- Minimise: Cost, CO_2e, use of undesirable processes.
- Maximise: Energy recovery, energy production, electricity recovery, electricity production, heat production, materials recovery.
- Throughput goal performance.
- Constraint performance.

Throughput goal performance is a measure of how well a waste flow type or material is optimised and a constraint performance is how well the system meets set constraints.

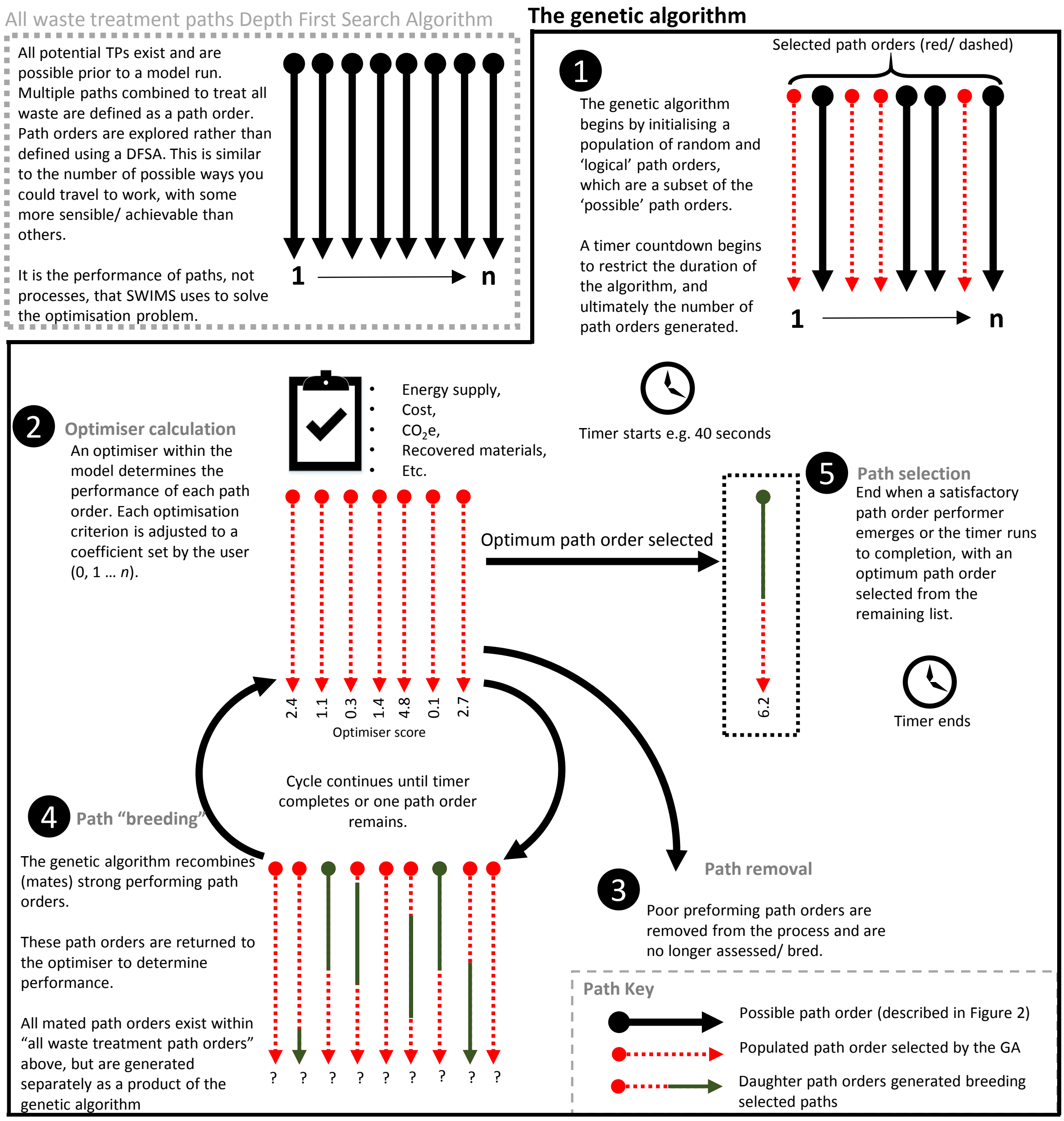


Figure 3. Schematic diagram of the genetic algorithm (GA) used to optimise WTP selection in SWIMS.

The worst performing parents are removed, while the path orders of the best performing parents are 'bred' together to create a new generation of path priority orders, referred to as "children". Successive generations of children are sorted based on their performance. As before, the worst performers are removed and the best performers bred until either only one optimum path order remains or a pre-defined time limit is reached, after which the best performing path order at that point is selected from the population. Only path orders that satisfy the model conditions are tested by the GA.

2.9 Additional capacity requests

After the GA has run for a timestep, as shown in Figure 4, and the outputs have been recorded, the amount of future capacity that is needed is calculated. For this, SWIMS calculates waste arisings for future years (see Section 2.4) and calculates the amount of useable infrastructure capacity (i.e. operational, upgradable or planned) in future years. User-defined planning horizons determine for how many timesteps the model will project forward and plan. The example shown in Figure 4 uses a planning horizon of five years to determine future waste arisings and infrastructure capacity (Point 1) and a planning frequency of one year timesteps, resulting in each year of the model run determining future capacity needs. This information is then used by the DFSA and GA (see Figure 3) to determine if it is possible to treat all generated waste within the planning horizon, while considering present and future constraints. Using the optimum path orders, SWIMS will determine the existence and size of any treatment capacity shortfall. Additional capacity requirements are generated using this data, for use in the infrastructure builder.

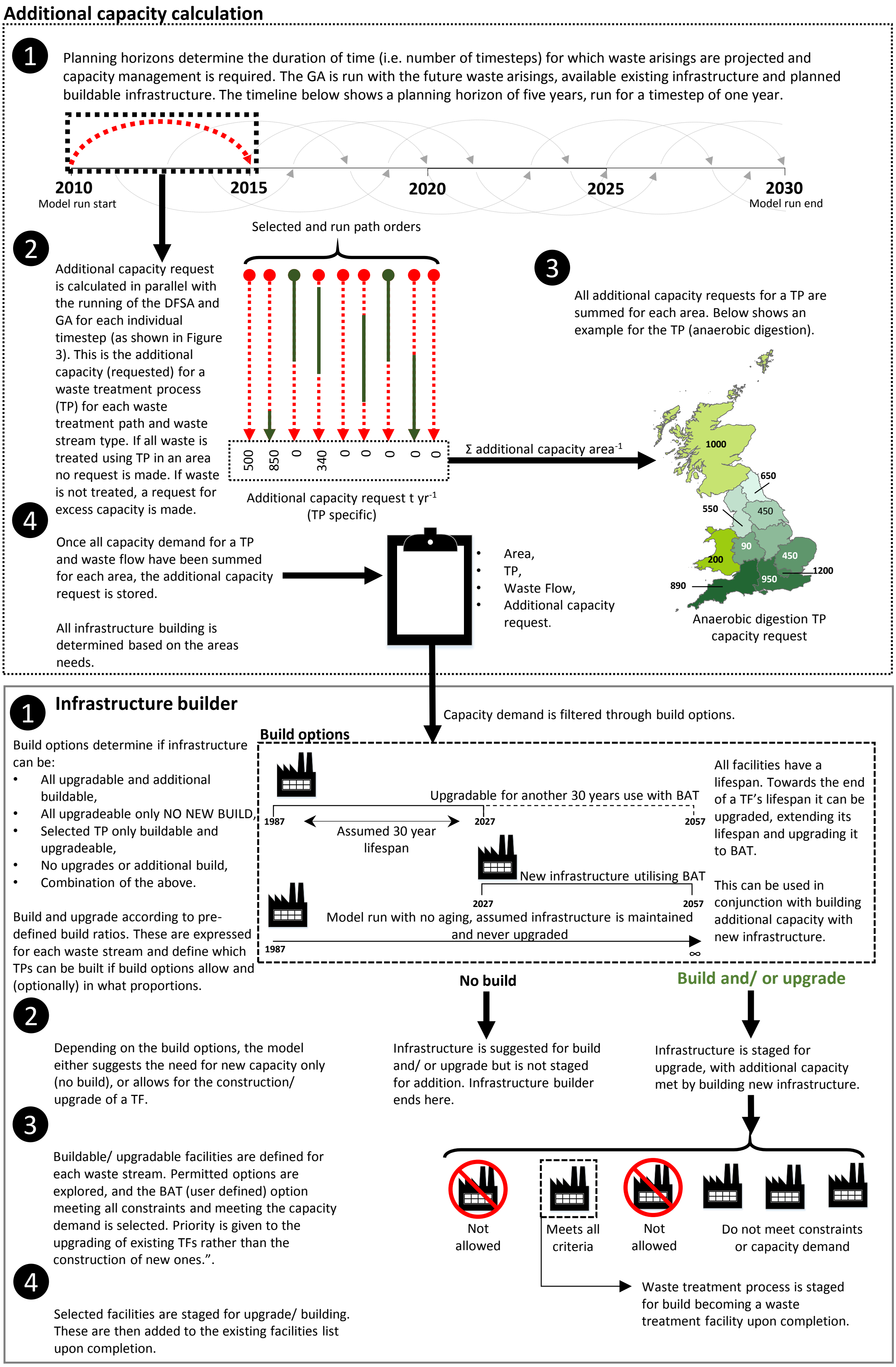

Additional capacity calculation
1
Planning horizons determine the duration of time (i.e. number of timesteps) for which waste arisings are projected and capacity management is required. The GA is run with the future waste arisings, available existing infrastructure and planned buildable infrastructure. The timeline below shows a planning horizon of five years, run for a timestep of one year.
2010
Model run start
2015
2020
2025
2030
Model run end
2
Additional capacity request is calculated in parallel with the running of the DFSA and GA for each individual timestep (as shown in Figure 3). This is the additional capacity (requested) for a waste treatment process (TP) for each waste treatment path and waste stream type. If all waste is treated using TP in an area no request is made. If waste is not treated, a request for excess capacity is made.
Selected and run path orders
500 850 0 340 0 0 0 0 0
Additional capacity request t yr-1
(TP specific)
Σ additional capacity area-1
3
All additional capacity requests for a TP are summed for each area. Below shows an example for the TP (anaerobic digestion).
1000
650
550
450
90
200
450
1200
950
890
Anaerobic digestion TP capacity request
4
Once all capacity demand for a TP and waste flow have been summed for each area, the additional capacity request is stored.
All infrastructure building is determined based on the areas needs.
• Area,
• TP,
• Waste Flow,
• Additional capacity request.
1
Infrastructure builder
Capacity demand is filtered through build options.
Build options determine if infrastructure can be:
• All upgradable and additional buildable,
• All upgradeable only NO NEW BUILD,
• Selected TP only buildable and upgradeable,
• No upgrades or additional build,
• Combination of the above.
Build and upgrade according to pre-defined build ratios. These are expressed for each waste stream and define which TPs can be built if build options allow and (optionally) in what proportions.
Build options
Upgradable for another 30 years use with BAT
1987
2027
2057
Assumed 30 year lifespan
New infrastructure utilising BAT
2027
2057
Model run with no aging, assumed infrastructure is maintained and never upgraded
1987
∞
All facilities have a lifespan. Towards the end of a TF's lifespan it can be upgraded, extending its lifespan and upgrading it to BAT.
This can be used in conjunction with building additional capacity with new infrastructure.
2
Depending on the build options, the model either suggests the need for new capacity only (no build), or allows for the construction/ upgrade of a TF.
No build
Infrastructure is suggested for build and/ or upgrade but is not staged for addition. Infrastructure builder ends here.
Build and/ or upgrade
Infrastructure is staged for upgrade, with additional capacity met by building new infrastructure.
3
Buildable/ upgradable facilities are defined for each waste stream. Permitted options are explored, and the BAT (user defined) option meeting all constraints and meeting the capacity demand is selected. Priority is given to the upgrading of existing TFs rather than the construction of new ones.".
Not allowed
Meets all criteria
Not allowed
Do not meet constraints or capacity demand
4
Selected facilities are staged for upgrade/ building. These are then added to the existing facilities list upon completion.
Waste treatment process is staged for build becoming a waste treatment facility upon completion.

Figure 4. Schematic diagram of the approach for determining additional capacity requirements in SWIMS.

2.10 Infrastructure builder

Requests for additional capacity are sent to the infrastructure builder, which will select the optimum waste treatment process(es) to meet this capacity demand. Selection is based on the following: the waste stream for which treatment capacity is required; user-defined constraints on (waste stream-specific) buildable waste treatment processes; the availability of upgradable, existing waste treatment facilities; and, capital budget. The selected process(es) are then staged for building, as illustrated in Figure 4, and made available for model runs of successive planning horizons to avoid multiple builds.

2.11 Waste transportation

All waste flows involve the transfer of waste from an origin to a destination. Inter-area transportation is required where waste is transferred between facilities in different geographic areas (e.g. London to the South East). Inter-area transportation is currently modelled based on the central geographic point for each area and the distances between these nodes. Larger vehicles are used for these transfers. Intra-area transportation has pre-defined collection/ transportation vehicles and distances based on discard rules and collection methods. Transport metrics are calculated from coefficients on a t km^{-1} basis.

2.12 Modelling of financial costs

Although comprehensive cost assessment methods, such as the approach proposed by Martinez-Sanchez *et al.* (2015), provide users with a detailed insight into the costs of their waste management systems, they are typically highly data-intensive. Given the challenges of acquiring comprehensive, accurate cost data for waste management processes, it was not considered appropriate to use such a detailed approach here (at least for SWIMS v.1). Rather, a simplified approach based on gate fees (for operational expenditure) and capital expenditure was followed. The gate fee is a unit payment made by the waste treatment/collection authority to the service provider that is charged against a given quantity of waste (typically £ per tonne) received at a TF. Gate fees may be positive or negative and are levied to cover the costs of operation, maintenance, and eventual closure of the site, and may be offset by the profits from the sale of recovered materials and/or energy (see Hogg (2002)). Gate fees have been used as a basis for comparing costs of alternative waste treatment options in the EU (Hogg, 2002) and the UK (WRAP, 2017). Capital expenditure is derived from one-time construction-related capital costs for the building of a new TF and upgrading an existing TF (by default, 50% of the build cost).

2.13 Modelling of environmental impacts

Potential environmental impacts of the SWM system are calculated using life cycle assessment (LCA), following an “attributional” approach (Heinrich, 2010). The assessment includes impacts from waste collection and treatment, as well as those on processes in external systems that are affected by the consequences of SWM activities, chiefly the recovery of materials and energy. The functional unit of the LCA is the treatment of all waste generated in an area within the planning time horizon, and the system boundaries are defined by the SWM system under investigation. The model follows the “zero burden assumption”, whereby the potential impacts from upstream life cycle stages prior to waste collection are not included, which is largely outside the remit of infrastructure planers and policy makers on waste management infrastructure (Ekvall *et al.*, 2007). Environmental impacts from capital goods (machinery, buildings, etc.) are not considered as they are typically negligible, in terms of Global Warming impacts, compared with those associated with TF operations (Brogaard and Christensen, 2016).

The basis of LCA modelling in SWIMS is a series of waste treatment process models, developed based on those developed for the EASETECH waste-LCA software (Clavreul *et al.*, 2014). Emissions are calculated for each waste collection and treatment process based on the composition and quantity of the input waste stream. Gross emissions are generated through the use of materials, energy and services during handling. Avoided emissions result from the production of electrical and thermal energy, soil improvers, and secondary materials that offset production from virgin materials (see Turner *et al.* (2016) for details of the modelling approach). Net emissions are calculated as differences between the gross and avoided emissions. Default life cycle inventory (LCI) data for the waste treatment processes pre-defined in SWIMS are provided in the SI.

Emissions to the environment, calculated here by the LCA process models, are translated into potential environmental impacts by applying substance-specific characterisation factors. These express the individual contribution of each emitted substance to a given impact category, relative to a reference flow (i.e. a waste flow). A wide variety of impact categories may be considered in LCA, such as freshwater eutrophication, human- and eco-toxicity and abiotic resource use. While SWIMS has the functionality to calculate impacts from as many substances and across as many impact categories as desired, the first version of the model is limited to considering only the potential impacts of greenhouse gas emissions on climate change. GHG emissions are characterised by Global Warming Potential (GWP) using a 100 year time horizon and expressed as tonnes of carbon dioxide equivalents (t CO_2e). Characterisation factors were taken from the baseline model of 100 years of the

Intergovernmental Panel on Climate Change (IPCC) (Bogner *et al.*, 2008). Only emissions of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) are considered. Combined, emissions of these three GHGs account for over 90% of total GHG emissions from SWM (Bogner *et al.*, 2008).

2.14 Modelling of regulatory and legislative requirements

The SWIMS model allows users to create specific constraints that enable analysis and exploration of different SWM policies and regulatory and legislative requirements. These include, landfill diversion targets for biodegradable waste, restrictions on the treatment of certain materials via certain processes (e.g. plasterboard waste to landfill), taxes (e.g. landfill tax or carbon tax). The performance of hypothetical systems based on different collections of constraints can be explored through use of scenario analysis; a powerful decision- and policy-support feature.

3. Case study

The illustrative case study was implemented using the C# scripting language and solved on a 64 bit Windows 8.1 machine with an Intel Core i7-6820HQ CPU, 2.7 GHZ processor and 16 GB RAM. The solve time was 55 minutes. All input database tables and complete output results tables can be found in the SI.

Here we present the coarse-grained, proof of concept results generated by SWIMS as part of a pilot test for the UK national infrastructure needs assessment (Hall *et al.*, 2016a). The data generated utilised a version of SWIMS run within the system-of-systems model, NISMOD 1 (National Infrastructure Systems MODel version 1) (Hall *et al.*, 2016b), developed by the Infrastructure Transitions Research Consortium (ITRC).

3.1 Model setup and data input

The model was based on a single, central (median) scenario of projected population growth, economic development and fossil fuel prices for GB (generated by an exogenous economic and demographics model (Hall *et al.*, 2016b)). Details of the scenario are described in Hall *et al.* (2016b) and the inputs used are presented in the SI. For the case study, only a "business as usual" (BAU) strategy was examined, with all current practices kept and only planned policy changes implemented. To remove the effects of inflation all calculations are at 2010 prices. Barring landfills, which have a finite capacity, the simulation of infrastructure aging was not considered, i.e. lifespan was set to "null" and all existing infrastructure remained operational until 2050. This was used as a means of estimating if current infrastructure (if well maintained) would be sufficient to meet future demand.

The database and LCI used are outlined in Section 2 and the SI. The model run considered the generation, collection and treatment of municipal solid waste (MSW) from 2010 (base year) to 2050 for the eleven government office regions (GOR) of England, plus Wales and Scotland (treated as GOR equivalents for the purpose of the study). To remove the effects of inflation all calculations are at 2010 prices. Barring landfills, which have a finite capacity, the simulation of infrastructure aging was not considered, i.e. lifespan was set to "null" and all existing infrastructure remained operational until 2050. This was used as a means of estimating if current infrastructure (if well maintained) would be sufficient to meet future demand. For each GOR represented in the model, an initial population of TFs was defined, as well as a list of planned/under construction TFs that are scheduled to become operational in pre-defined future timesteps ($t > 0$). In total, the database contains information on 905 existing TFs and 182 planned TFs across GB. Details of each TF (including capacity) were estimated from publically available sources (e.g. waste permits, company reports, etc.). Details of all TFs are available within the SI.

The optimisation goal (objective function) of this model run was to minimise financial costs. Note, though, that whilst a single optimisation goal is used for this demonstrative case study, SWIMS does allow for multi-objective optimisation. Transfers of waste among GORs and the export of recyclate and refuse-derived fuel abroad were both enabled. UK landfill tax was considered dynamically. An overview of all constraints utilised in this case study is outlined in Table 1. Note that as SWM is a devolved issue in GB, different constraints are utilised for England, Scotland and Wales (constraints 1-9, 10-20 and 20-24, respectively).

Constraint number	Waste throughput type	Initial time step	Final time step	Operator	Value	Value type	Source
1	Recycling & composting	2010	2014	>=	0.4	proportion	(European Union, 1999, 2008)
2	Recycling & composting	2015	2019	>=	0.45	proportion	(European Union, 1999, 2008)
3	Recycling & composting	2020		>=	0.5	proportion	(European Union, 1999, 2008)
4	Recycling, composting & energy recovery	2010	2014	>=	0.53	proportion	(European Union, 1999, 2008)
5	Recycling, composting & energy recovery	2015	2019	>=	0.67	proportion	(European Union, 1999, 2008)
6	Recycling, composting & energy recovery	2020		>=	0.75	proportion	(European Union, 1999, 2008)
7	Biodegradable waste to landfill	2010	2012	<=	11,200,000	mass (tonnes)	(European Union, 1999, 2008)
8	Biodegradable waste to landfill	2013	2019	<=	14,510,000	mass (tonnes)	(European Union, 1999, 2008)
9	Biodegradable waste to landfill	2020		<=	10,160,000	mass (tonnes)	(European Union, 1999, 2008)
10	Biodegradable waste to landfill	2010	2012	<=	1,320,000	mass (tonnes)	(European Union, 1999)
11	Biodegradable waste to landfill	2013	2019	<=	1,798,000	mass (tonnes)	(European Union, 1999)
12	Biodegradable waste to landfill	2020		<=	1,258,000	mass (tonnes)	(European Union, 1999)
13	Reuse & recycling	2020		>=	0.5	proportion	(European Union, 1999; SQWenergy, 2010)
14	Energy from waste	2010		<=	0.25	proportion	(European Union, 2008; SQWenergy, 2010)
15	Waste to landfill	2025		<	0.05	proportion	(European Union, 1999; SQWenergy, 2010)
16	Recycling & composting	2010	2012	>=	0.4	proportion	(European Union, 2008; SQWenergy, 2010)
17	Recycling & composting	2013	2019	>=	0.5	proportion	(European Union, 1999; SQWenergy, 2010)
18	Recycling & composting	2020	2024	>=	0.6	proportion	(European Union, 2008; SQWenergy, 2010)
19	Recycling & composting	2025		>=	0.7	proportion	(European Union, 1999; SQWenergy, 2010)
20	Biodegradable waste to landfill	2010	2012	<=	710,000	mass	(European Union, 1999)
21	Biodegradable waste to landfill	2013	2019	<=	919,000	mass	(European Union, 1999)
22	Biodegradable waste to landfill	2020		<=	643,000	mass	(Welsh Assembly Government, 2009)
23	Reuse & recycling	2020		>=	0.5	proportion	(Welsh Assembly Government, 2009)
24	Reuse & recycling	2025		>=	0.7	proportion	(Welsh Assembly Government, 2009)

Table 1. All constraints utilised within this SWIMS model run.

3.2 Interpretation of model outputs

Arisings of MSW were calculated based on regional GVA and waste generation coefficients, as outlined in Section 2. Figure 5 shows the main outputs from the model run. A gradual decrease over time in the amount of waste generated (Figure 5a) is observed in 10 of the 11 GOR. This is due to the rates of waste decoupling (from GVA; see Section 2.4) in those GOR being greater than the rates of population growth. In contrast, the population increase in London is predicted to be such that there is an increase in waste generation over time.

Figure 5b shows a decline in the amount of “overflow waste treatment” (defined as being any waste that is sent to landfill) between 2010 and 2020, with a further slight decline after 2020 in all GOR except London, again due to greater population growth in this region. These declining amounts of overflow waste treatment are a consequence of the model responding to constraints imposed by regulatory and legislative instruments that set limits on the amount of waste that can be sent to landfill each year (Waste framework directive targets for recyclate material recovered and waste to landfill, see SI).

The amount of treated waste that is recovered for recycling is shown in Figure 5c. After initial fluctuations during the infrastructure build period 2010-2020, recycling rates begin to stabilise, with slight variations among GORs. Post-2020, as new infrastructure is built and constraints are met, the amount of recovered material begins to increase. Similar trends are observed for energy production from waste, which is the result of new thermal treatment facilities becoming operational by 2020.

The climate impacts of SWM decline from 2010 to 2015 (a reduction of around 4.5 Mt CO_2e). Post-2015, this culminates in a net “positive” climate impact reduction, i.e. climate benefit; a consequence of the increased avoided climate impacts from energy production and materials recycling (Figures 5g-h). The greatest “positive” effects are observed in the East of England, which is likely due to a combination of increased material and energy recovery in the region as well as lower waste production compared to other GORs. Gradual increases in climate impacts in some GORs are observed post-2020. This is due to a decrease in waste arisings, which reduces the amount of waste available from which energy and recyclable materials can be recovered (i.e. reducing the potential for causing avoided climate impacts). To combat this (perhaps, misleading) effect, climate impacts can also be measured per tonne of waste generated (Figure 5h). For example, a region that produces more primary waste, such as London, could displace more CO_2e in total, but might displace less CO_2e when measured on the basis of CO_2e per tonne of waste produced.

Figures 5b-h show the amounts of waste treated in each year in each GOR between 2010 and 2050. Large fluctuations are observed between 2010 and 2020, which is due to heavy initial investment in infrastructure by the model in 2011 (shown in Figure 5f) – in order to meet current and future constraints – and new infrastructure (including both that which was planned prior to 2010 and that which was built by the model in 2011) becoming operational at various times until 2020 (Figure 5f).

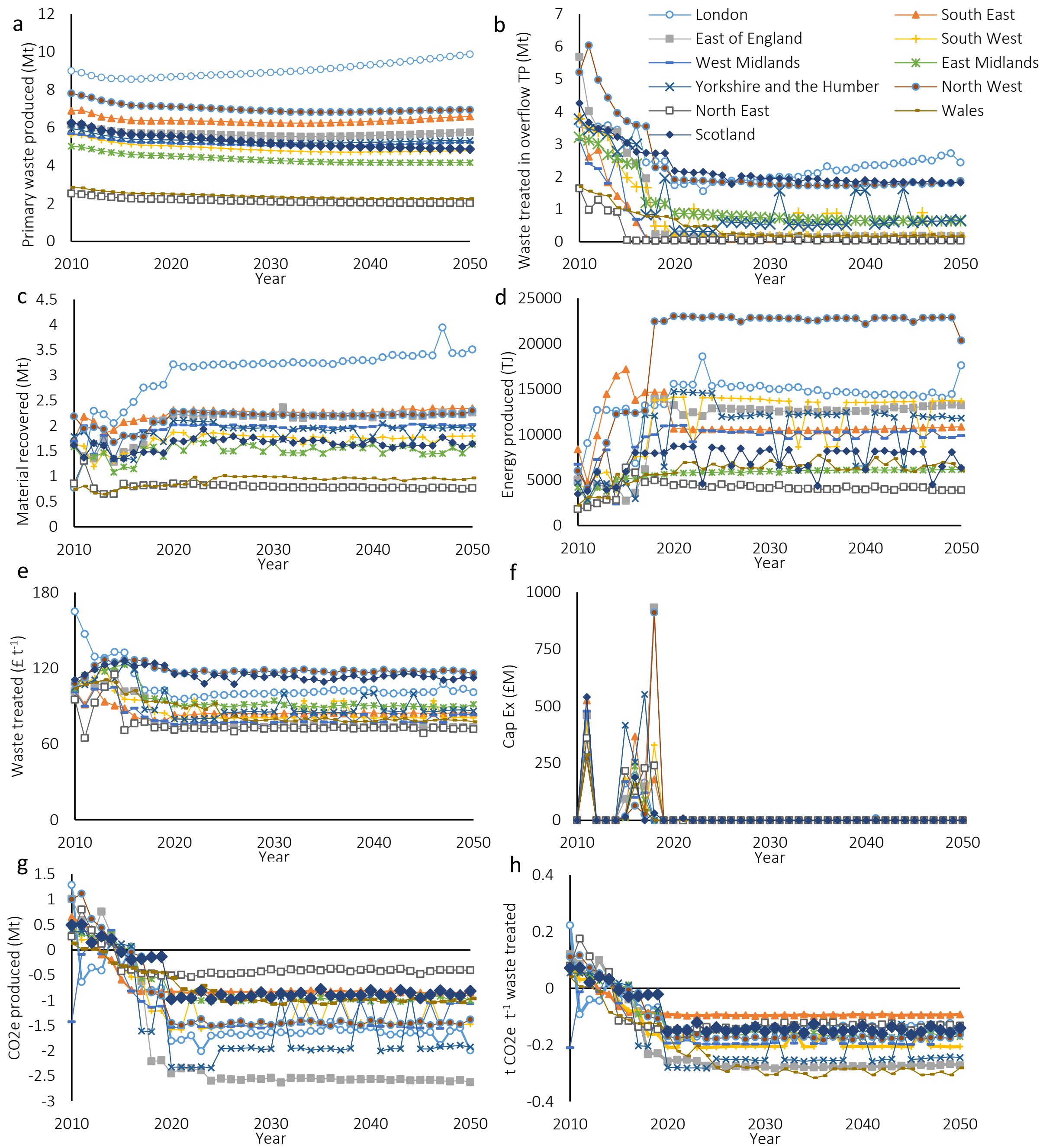


Figure 5. Model output for the case study, representing a BAU scenario covering eleven GOR within GB. 5a shows the tonnes of waste treated as overflow, 5b shows the tonnes of primary waste treated, 5c shows the tonnes of material recovered, 5d shows the energy produced in each region (TJ), 5e shows costs in £ tonne^{-1} waste treated, 5f shows the capital expenditure, 5g shows the tonnes of CO_2e produced, and 5h shows the tonnes of CO_2e produced per tonne of waste treated.

Total operational expenditure is significantly greater than capital expenditure, as shown in Figure 6. This highlights the significance of optimising the treatment paths when compared to determining the correct infrastructure needs. There is a significant variation in regional operational costs; this is due to a combination of differing total waste arisings, collection and transport methods and distances, as well as initial available TF infrastructure.

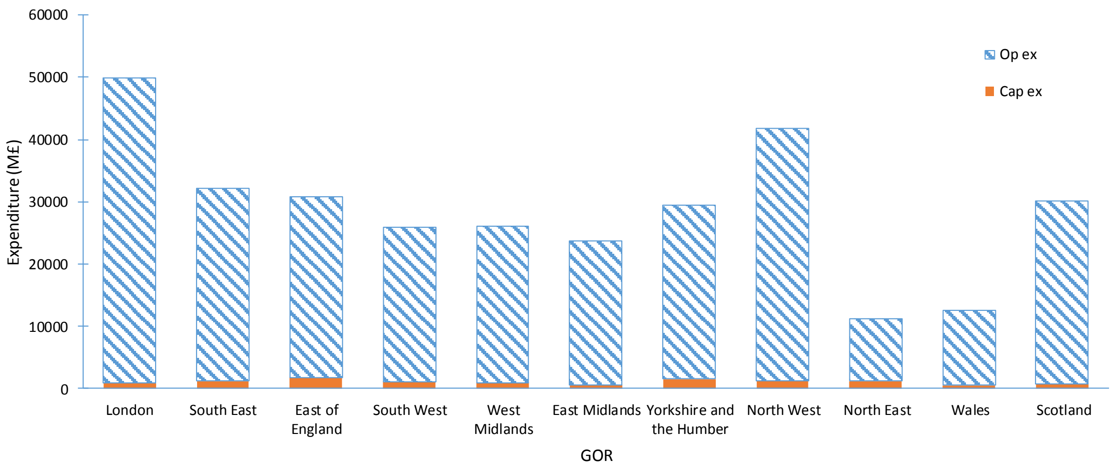


Figure 6. Total operational and capital expenditure for each GOR between 2010 and 2050.

Simulated capital expenditure peaks in 2011 (Figure 5f), which is due to the initial sizeable investment in materials recycling facilities, as shown in Figure 7. Such investment is necessary for the system to handle the ever-increasing demand for recycling capacity in future years and to meet constraints on landfill rates and recycling targets. Overall, a diverse mix of waste treatment process types was constructed for each GOR, reflecting the unique requirements and situation of each region. Construction focussed primarily on facilities for materials recycling (as mentioned above) and the biological treatment of organic material (e.g. composting and anaerobic digestion facilities). The simulated capital expenditure for Scotland is far higher than might be expected. In other GORs a large number of facilities become operational post-2010 but construction was agreed and capital expenditure was paid prior to 2010, i.e. capital expenditure is not paid during the simulation time period. To meet capacity demands in the ensuing years, relatively little further investment in infrastructure is required in those regions. In contrast, there is a relative lack of such planned facilities in Scotland, which therefore requires greater investment in infrastructure post-2010 in this region. Finally, it should be noted that no landfills were staged for construction in any GOR post-2010, despite them being the only facilities that would require replacement due to their finite capacity (Figure 7). This suggests that there will be sufficient capacity from existing and planned infrastructure in GB to handle future demand for residual waste treatment, at least in this simulated BAU scenario.

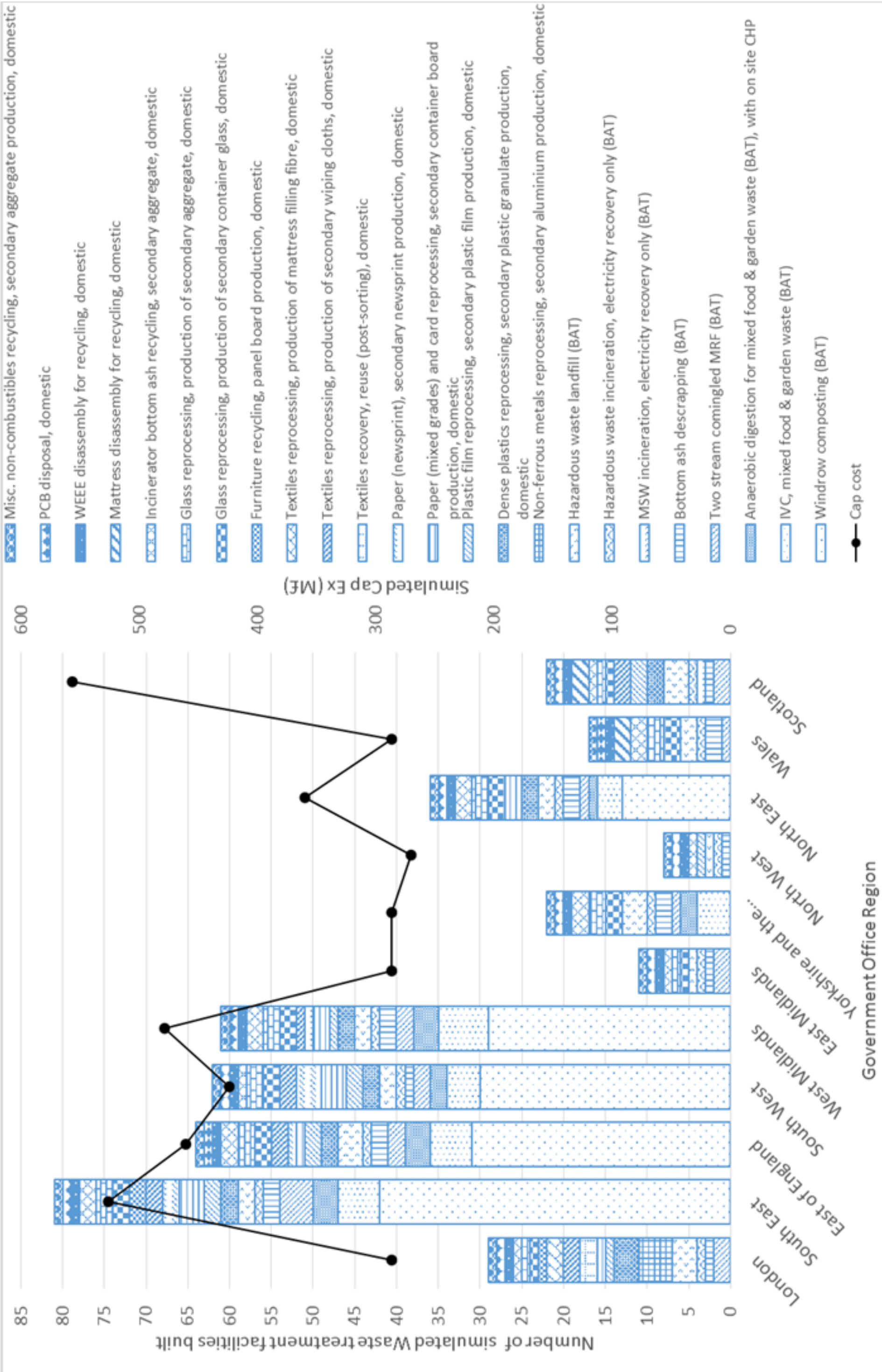


Figure 7. Total simulated capital expenditure and the number and type of facilities built for each GOR.

3.3 Case study findings and conclusions

Four principle conclusions can be drawn from the presented case study:

1. Relatively little capital investment in additional infrastructure is required to meet the SWM demands of a central BAU scenario for all GOR. However, this is based on the assumption that all planned and existing infrastructure is maintained until 2050 with no additional costs beyond operational expenditure. Where capital investment in additional infrastructure was required, it was largely to meet increased demand for materials recycling and organic waste treatment facilities.
2. Operational costs varied widely between regions, primarily due to differences in waste generation rates and the availability and types of existing/planned facilities that are/will be available to meet SWM demands.
3. Sufficient capacity is available through existing and planned infrastructure to ensure that all targets for reducing the landfilling of wastes are met and that there is an overall reduction in the amount of waste that is sent to landfill in all regions compared with 2010 levels. This is achieved through a simultaneous increase in both material recycling and energy production from waste over time.
4. The climate impacts of SWM were found to decline over time in all regions, with SWM in GB eventually having a net "positive" climatic effect, i.e. environmental benefit. This is due to the aforementioned increase in material and energy recovery, which offsets the need for virgin materials in product manufacturing, and fossil fuels in energy generation.

Detailed outputs of the modelled scenario are available in the SI.

4. Concluding remarks

SWIMS is a dynamic, non-linear, life cycle-based tool for optimising SWM in a given region (or given regions) over a defined time period, determining future capacity requirements, and identifying optimum infrastructure solutions to meet future capacity demands. Unlike traditional, linear optimisation tools for SWM, waste flows through the network are modelled in SWIMS heterogeneously and with distinct and dynamic compositions; ratio constants based on non-linear expressions are defined for each waste material and each waste treatment process type. This modelling approach results in a combinatorial NP-Hard optimisation problem that is addressed through a sequential evolutionary genetic algorithm. Optimisation can be based to one or multiple objective function(s) and with respect to all constraints placed on the system. SWIMS therefore addresses the need for an algorithm to efficiently solve non-linear optimisation problems for large-scale SWM system models (Kumar *et al.*, 2010) and enables more complete and thorough assessments of the economic and environmental performance of SWM systems.

SWIMS can be used to provide valuable information for SWM decision- and policy-makers, particularly when used to analyse the systemic effects of possible future national or regional policies. To demonstrate the tool's functionality, an illustrative case study of MSW management in GB from 2010 to 2050 was presented. Results show that waste generation is projected to decline in most GOR, with the exceptions of London, South East England and the East of England. The model suggests that sufficient capacity is available in existing and planned infrastructure to cope with current and future demand for SWM and meet the UK's regulatory and legislative requirements with relatively little capital investment beyond 2020. A single scenario for population and economic growth, and a "business as usual" strategy was examined in the study, but the flexibility and adaptability of SWIMS enables a multitude of scenarios and strategies to be explored, whilst the database can be modified to reflect the specific needs of the user. For example, planners could explore the impact of policies to further reduce waste generation versus relying on infrastructure solutions; this is particularly relevant in areas of increasing population growth.

The SWIMS approach enables the user to examine the resilience of a complete system at a materials level with varying constraints, and economic and environmental drivers, while addressing the unique relationships of different material types and combinations. SWIMS will optimise the pathways to which waste is managed as opposed to the conventional management of facilities. This allows for a fine grained analysis of the impacts of altering waste material composition within the current, and evolving, infrastructure. Policies and legislation such as the incorporation of EU circular economy package or the UN sustainable development goals can be simulated with a plethora of scenarios and strategies to understand both environmental and economic impacts. .

The current version of SWIMS has several limitations that will be addressed in future updates. The model is limited by the availability of LCI data on different waste treatment processes. Capital goods (machinery, buildings, etc.) are not currently considered in the modelling of environmental performance due to a lack of available data and their typical insignificance in terms of the potential global warming impacts of SWM (Brogaard and Christensen, 2016). It has, however, been shown that these impacts can be significant to the overall environmental impacts of SWM (Brogaard and Christensen, 2016). To enable users who wish to extend the LCI assessment beyond the one currently considered impact category, global warming, and relevant LCI data should be identified and integrated into the tool.

An inherent consequence of the dynamic, future-oriented nature of SWIMS is that the uncertainly will increase quite drastically as the model runs into the mid- to long-term. Most treatment processes are currently modelled in two technology levels: “average” and “best-available”. However, a lack of knowledge of how technologies will advance in the future, limits the likely representativeness of the model over long time horizons. This is also true of the data and modelling approach used for transportation and collection options, which will likely be affected by changes in fleet composition and engine type in the future (e.g. increasing share of electric vehicles). Similarly, the modelling approach to waste generation, which is based on a decoupling rate that relates arisings to population and economic growth, becomes increasingly problematic over time. Whilst data on waste arisings have been regularly collected in the UK since the 1990s, the decoupling rates applied in the case study are based on short temporal trends (c. 15 years), which leads to uncertainty regarding the robustness of such relationships in the mid- to long-term. Furthermore, the overall approach to modelling waste generation is valid only if there a relationship between these variables exists, which may not be valid in all cases, both now and in the future. Future versions of SWIMS with appropriate data input will enable rates to be changed over time, e.g. to represent increasing waste reduction rates.

An important limitation concerns the approach used to model financial costs, which is highly simplified in the current model and can be improved in future versions, provided that sufficient relevant data becomes available.

The LCA modelling approach is deterministic and does not account for uncertainty in the model input, nor is sensitivity or uncertainty in model output considered. This can be improved through the implementation of stochastic analysis, although this would also require significantly more data on input variables. Regarding the cost assessment, operational expenditure is currently based on gate fees, which incorporate a highly aggregated range of costs and are highly variable between regions and facilities. Access to, and inclusion of, data on operational costs for different waste treatment technologies and collection methods would significantly improve the representativeness of the model; such data are, however, scarce. SWIMS has been designed in such a way that it can easily modified by software developers and users, which provides considerable flexibility in how and where it can be used. It can also be utilised in its standalone form or be integrated with other infrastructure software packages as part of a system-of-systems model (see, for instance, its use in NISMOD1 as part of the ITRC research consortium (Hall et al, 2016b)). Such integrated modelling can be highly beneficial, for instance integration of SWIMS with an energy system model can enable the exploration of cross-sectoral impacts of energy from waste processes, which is relevant for decision makers in both the energy and waste sectors.

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Supplementary information

SI including the database and results outputs is available from

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