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METHODS, TOOLS, DATA, AND SOFTWARE

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Machine learning-based stocks and flows modeling of road infrastructure

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Abstract

This paper introduces a new method to account for the stocks and flows of road infrastructure at the national level based on material flow accounting (MFA). The proposed method closes some of the current shortcomings in road infrastructures that were identified through MFA: (1) the insufficient implementation of prospective analysis, (2) heavy use of archetypes as a way to represent road infrastructure, (3) inadequate attention to the inclusion of dissipative flows, and (4) limited coverage of the uncertainties. The proposed dynamic bottom-up MFA method was tested on the Norwegian road network to estimate and predict the material stocks and flows between 1980 and 2050. Here, a supervised machine learning model was introduced to estimate the road infrastructure instead of archetypical mapping of different roads. The dissipation of materials from the road infrastructure based on tire–pavement interaction was incorporated. Moreover, this study utilizes iterative classified and regression trees, lifetime distributions, randomized material intensities, and sensitivity analyses to quantify the uncertainties.

KEYWORDS
bottom-up modeling, dynamic modeling, geographic information systems (GIS), industrial ecology, machine learning, material flow analysis (MFA)

1 | INTRODUCTION

A large number of construction materials have accumulated as part of road infrastructure over the past decades (Wiedenhofer et al., 2015) that has partly been due to the expansion, upgrading, and rebuilding of the road infrastructure system over time. Simultaneously, road infrastructures undergo various maintenance activities during their service lives, with the main purposes to increase safety, decrease capital expenditure, and improve quality of travel (Kallas, 1985). Concerning the continuous demand for construction materials for road infrastructure, it is of importance to know how much has accumulated and how much will be needed to cope with the current demand.

Material flow accounting (MFA) is a well-established method that helps estimate and predict the stocks and flows of materials on different spatial and temporal scales within a defined system. A large number of MFA studies in the area of construction materials have focused on buildings, see for instance Sandberg et al. (2016). However, a gradual trend has started to emerge in the MFA of transport infrastructure to understand the behavior of the system (with respect to the flows and accumulation of materials) and gain insights into the availabilities in terms of quantities and time for secondary materials to theoretically substitute virgin materials; see for example, Wiedenhofer et al. (2015).

Depending on the goal and scope of the MFA of transport infrastructure, different modeling approaches have been considered in prior studies (Augiseau & Barles, 2017). Despite the differences, three variables were constantly considered in MFA: level of analysis (top-down or bottom-up), type of model (static or dynamic), and period of assessment (retrospective, prospective, or a combination of both). Of the three, five typical sets of combinations were found in the literature reviewed (Guo et al., 2017; Han et al., 2018; Hashimoto et al., 2009; Hoffren et al., 2000; Huang et al., 2018; Kapur et al., 2008, 2009; Kovanda et al., 2007; Luukkanen & Kaivo-oja, 2001; Miatto et al., 2016, 2017; Schiller, 2011; Shi et al., 2012; Tanikawa & Hashimoto, 2010; Tanikawa et al., 2015; Wen & Li, 2010; Wiedenhofer et al., 2015). A summary is presented as Table S1 of Supporting Information S1.

Despite the utilization of MFA in road infrastructure, a clear majority of the prior research was limited to retrospective assessment, without forecasting the future of road infrastructure. The exclusion of the prospective assessment has created a void that limits the applicability of the MFA results to offer decision supports based on various scenarios. Besides, based on the findings of prior studies (Schiller, 2011; Wiedenhofer et al., 2015), a considerable amount of road materials are needed to maintain the roads in service. The greater demand for maintenance activities is a result of their relatively shorter lifespan causing a high material turnover. Knowing the fact that the roads that are in-service today need to be maintained at some point in the coming future stresses the importance of including the prospective assessment.

The use of archetypical mapping of road infrastructure has been a given approach in some earlier scholar works to represent most typical road infrastructure (Guo et al., 2014; Miatto et al., 2017; Tanikawa et al., 2015; Wiedenhofer et al., 2015). This modeling approach creates representative infrastructure sets to depict a cluster of road infrastructure that are identical due to their commonalities, like traffic volume, subgrade type, and number of lanes. However, archetypal mapping is often too rigid and oversimplifies infrastructure representation. Also, it can become too difficult and time demanding to create archetypes for every little variation when dealing with the networks of roads at the national level.

The loss of irrecoverable materials to the environment, which cannot be reused or recycled, has rarely been acknowledged in prior studies in the domain of road infrastructure, except for the study by Hashimoto et al. (2009). Quantification of the lost materials (also known as dissipation) has hardly been carried out in road MFA, as the losses are often difficult to estimate and constitute only a small share of the total outflows. Nevertheless, the importance of considering the dissipative flows has been highlighted through other MFA studies because they provide useful information, like the impacts of these flows on human health (Adamiec et al., 2016; Penka et al., 2018) and estimating the availability of future materials (Daigo et al., 2015; Haas et al., 2015; Hamilton et al., 2016; Hashimoto et al., 2009; Mayer et al., 2019).

Even though uncertainty analysis has been covered by other MFA studies, see for instance Cao et al. (2017), Fishman et al. (2018), and Wiedenhofer et al. (2019), uncertainties were not handled in the studies reviewed. The major reason for that was because of the use of fixed values rather than encompassing the deviations of the inputs. For instance, fixed lifetime was used used to explain the service lives of products, fixed design structure was used to determine the initial state of the infrastructure, and/or fixed values were used to explain the intensity of materials.

To close the identified gaps, this study proposes a supervised machine learning (ML)-based bottom-up dynamic MFA method that provides retrospective and prospective assessments along with the inclusion of dissipative losses and an analysis of the uncertainties. It uses the road networks in Norway as a case study to demonstrate its applicability and present the findings. The study focuses on three categories of roads, namely, European, national, and municipal. Additionally, it excludes road tunnels and bridges, and only considers nonmetallic construction materials, that is, bounded and unbounded materials.

2 | METHODS

Equations (1) and (2) were chosen in this study as they consider that the flows and stocks in each timeframe must be in equilibrium condition in the studied system (Kapur et al., 2008).

$$S(t) = S_0 + \int_0^t \dot{S}(t)\,dt \tag{1}$$

$$\dot{S}(t) = I(t) - O(t) \tag{2}$$

where S denotes the stock at time t, S_0 denotes the initial amount of stock, $\dot{S}$ denotes the changes in the amount of stock at time t (i.e., net addition to stock), I denotes the inputs to the system at time t, and O denotes the outputs from the system at time t.

This study proposes a model consisting of four main steps to account for the material flows and stocks of road infrastructure: (1) collection, (2) preparation, (3) modeling, and (4) analysis. The steps were carried out in this order by using the output from the preceding step as the input for the succeeding one. The overall flowchart and involving subcomponents are presented in Figure S3 of Supporting Information S1.

- Collection: relevant and available first-hand data.
- Preparation: first-hand data processed to prepare secondary data suitable for postprocessing.

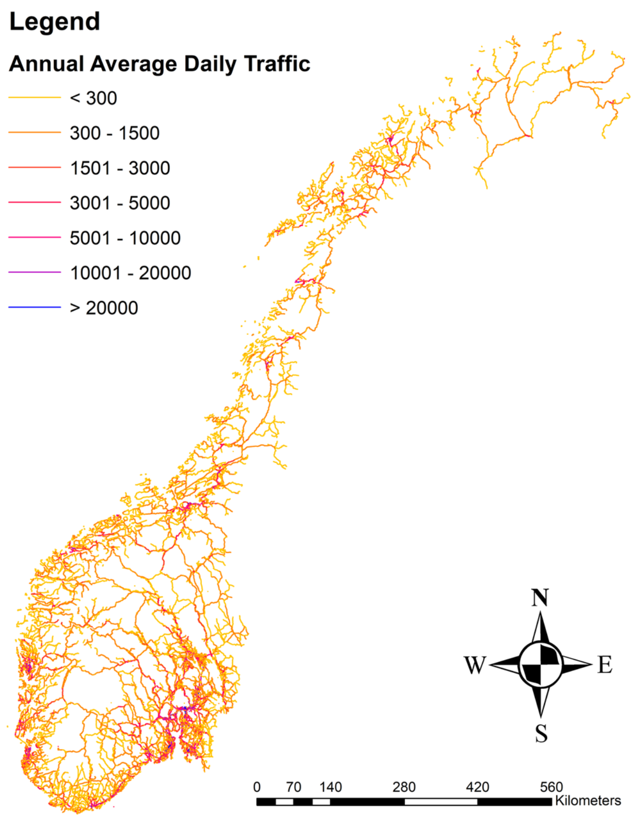

FIGURE 1 The road networks that were investigated in this study. The networks are color-coded according to the different traffic ranges recorded in 2017
Source: www.vegkart.no

- Modeling: six modeling approaches were considered: accounting for the number of road structures[1] (including the initial stock in 1980 and subsequent input and output stocks up to 2017), accounting for the historical maintenance activities (input and output until 2017), estimating the lifetimes of road materials, hypothesizing the future volume of traffic between 2018 and 2050, predicting the future of maintenance activities, and estimating and predicting dissipative flows between 1980 and 2050.
- Analysis: the model outputs were used to estimate the stocks and flows between 1980 and 2017 and predict them between 2018 and 2050.

Besides, the written scripts for this study can be found in the following Github address: https://github.com/babake/DynamicStockModelling_roadInfrastructure

2.1 | Collection: Raw input data

The Norwegian Road Database was used to obtain the data for this study (Andersen, 2015). Even though the database contains a wide range of historical data, only seven datasets were considered for the study, namely: road structure, paving history, road refinance, road width, speed limit, surface milling, and traffic volume (for more details see Section S2 of Supporting Information S1). The time period for the datasets was from 1980 to 2017.

The collected data covered both inner- and inter-city roads, which consist of EU, national, and county roads with a total length of about 55,000 km and a surface area of about 352 km^2 for the year 2017. Figure 1 shows the studied road networks, which represented the system boundary for the collected data.

[1] Road Structure is a compost of various layers (from the bottom being the frost protection course or subbase course all the way to the top, see Figure S4 of Supporting Information S1). Here, we called such a layer composition a "road structure."

2.2 | Preparation: Data processing

Based on earlier experience with the data (Ebrahimi et al., 2019), the most promising way to handle the data was to use geographical information systems. The FME Workbench version 2017.0 (Safe Software, 2017) was used for this purpose and several sequential steps were performed to prepare the data. The data processing intermediate steps are explained in Appendix S3 of Supporting Information S1.

2.3 | Modeling: Secondary data

The following sections explain the applied modeling approaches.

2.3.1 | Road structure

Despite the existence of data for the structure of roads, the dataset was limited to a few public roads, making it difficult to know about the dimensions of the pavement structure for the remaining ones. As this study aims to introduce an alternative approach to the archetypical modeling to make an estimation for roads with missing structural information, supervised ML is used to train, validate, and test data. The supervised learning (Bonnin, 2017) was performed layer by layer, starting from the first layer (being the nearest layer to the subgrade) and continuing to the next layer on the top (see Figure S4 of Supporting Information S1). Predictive variables were used to identify the determined response variables. The predictive variables for the first pavement layer were subgrade type, traffic volume (in unit of annual average daily traffic [AADT]), number of heavy vehicles, road category, and initially signed speed limit (the registered speed limit on the day the road was opened to the public). Also, the response variables were pavement material type and thickness. It is worthwhile to highlight that the selection of these predictive variables was based on common practice used in empirical pavement design (Huang, 2004).

As the first layer was predicted, its response information was added to the list of predictive variables and later used for the second layer. In other words, the pavement material type and thickness corresponding to the first layer became the predictive variables for the response variables corresponding to the second layer. This accumulative approach was continued up to the last layer, which allowed to estimate the overall dimensions of pavements. The repetitive process was continued until the fourth layer because the common road structures based on the registered data consisted of about four layers.

Among the different supervised modeling approaches, the decision tree models were chosen (Barros et al., 2015). Table S2 of Supporting Information S2 compares the results of the decision tree models with other models. The classification tree model was used to estimate the road layer types, whereas the regression tree model was used to estimate layer thicknesses. Both models follow a recursive partitioning method (by breaking down the entry data into smaller subsets), which in the end results in a tree with leaf nodes and decision nodes (Barros et al., 2015). A leaf node indicates a class while a decision node carries out tests on a single attribute.

The Gini diversity index (Han et al., 2011) was used for the decision tree models to measure the impurity of partitioning in each decision node (D). It measures the diversity of the output classes in a training set. The selection is based on features resulting in subsets with more homogeneous output variables, that is, the best split-variable value. Equation (3) expresses how the Gini index measures the impurity of a partitioning feature.

$$Gini(D) = 1 - \sum_{i=1}^{m} P_i^2 \tag{3}$$

where P_i is the probability of partitioning feature D belonging to a class set (for $i = 1, \ldots, m$) and the sum is computed over m distinct classes.

Both classification and regression tree models were trained in MATLAB R2017b (MathWork, 2019). Uncertainty assessment of the estimation was integrated into the regression tree model to reveal the variations in the estimated results. The training and testing of data involved 100 iterations for a determined pavement layer. The training testing ratio of 50:50 was used, which means that in each round, only 50% of the data were used for training, and later, for estimation.

After estimating the layer thickness and composition for different sections, the mass of the road structure at different sections between 1980 and 2017 was calculated. A range for the densities of the different road materials was specified to ensure that the results from the equation account for the uncertainties and are not limited to fixed values. Uncertainty was calculated with the help of the continuous uniform distribution. The selected random densities for each layer in each section was based on 100 rounds of iteration. The uniform distribution was chosen because the distribution of the material densities was unknown. Hence, the distribution considered equal probabilities for the randomly selected densities within a determined range to minimize subjectivity. Appendix S4 of Supporting Information S1 provides the equation used to calculate the road structure mass.

Based on existing data, it was not possible to distinguish between in-service and out-of-service road infrastructures. Hence, in this study, it was considered that decommissioned roads should be classified as out-of-service infrastructure and shown as outflows of the in-service road stocks. Therefore, stocks represent only in-service road infrastructure.

2.3.2 | Lifetime estimation

To predict the probability of maintenance activities for in-service pavements, it is essential to understand their longevity. Among the various statistical models available to estimate the lifetimes of pavement materials, this study used the Cox proportional hazard (PH) model (Cox, 1972). This model is a branch of survival analysis that is semiparametric and tracks the risk (of failure) of an event over time without following a specific distribution of the hazard function.

$$h_i(t|Z) = h_{0i}(t)e^{(Z\beta)} \tag{4}$$

where h_i is the hazard rate, Z denotes a vector of covariates, h_{0i} denotes the baseline hazard stratified over i strata, and β denotes the vector of the coefficient measuring the impacts of covariates.

The potential of the semiparametric model was shown in prior research (Ebrahimi et al., 2019), and this study adopted a similar approach and considered the effect of different explanatory variables in the estimation of lifetimes. This means that the model was stratified based on traffic classes to obtain the estimated lifetimes.

In addition to the stratification of the semiparametric model, different distributional functions (e.g., lognormal, exponential, gamma, generalized gamma, and log-logistic) were tested to identify the most suitable fits. This approach was adopted to solve the issue of overfitted results in the semiparametric model. The Weibull function showed better results for the goodness of the fit tests (i.e., log-likelihood test and significance test) compared to those of the other distributional functions. Hence, the Weibull function was fitted to the semiparametric model to quantify the distributional lifetimes of road materials in different traffic volume classes.

The density function of a two-parameter Weibull distribution at time t can be written as

$$f(x|a,b) = \frac{a}{b}\left(\frac{x}{a}\right)^{b-1} e^{-(x/a)^b} \tag{5}$$

where x is a time variable, a denotes the scale parameter, and b denotes the shape parameter (both a and b only accept positive values).

2.3.3 | Traffic scenario

Generally, the average traffic volume on Norwegian roads has grown consistently. Although the rate might vary for different roads, the average yearly growth has been about 1.6% between 2005 and 2018, and it was predicted that the average annual traffic growth would be 1.5% in 2050 (Hovi et al., 2015). Continuous growth means an increase in cyclic loading and the need for maintenance activities may potentially increase.

As this study aimed to predict the future impact of traffic volume on the intensity of maintenance works (for pavements that were still in service at the end of 2017), three scenarios were considered: (1) Scenario 1: Traffic volume will stay constant after 2017; (2) Scenario 2: 1% annual growth in traffic volume by 2050; and (3) Scenario 3: 2% annual growth in traffic volume by 2050. This approach aimed to show how the change in traffic volume will result in a shift in the share of roads corresponding to the different traffic classes, which subsequently affects the intensity of maintenance works.

Based on the estimated results in Section 2.3.2, it was possible to predict how the maintenance activities would be conducted for the in-service roads beyond 2017. However, as was shown by prior research (Dong et al., 2016), the uncertainties in the prediction of maintenance activities heavily depend on the inclusion of independent variables that influence the lifetime of in-service pavements, like climate, material types, and traffic. A simplified approach was considered to capture the uncertainties in the prediction of future maintenance activities. Here, we only focused on the effect of traffic on the intensity of maintenance works. This was done because we found it very challenging to attain information related to microclimate along the roads. Furthermore, it remains an uncertainty on which paving materials will be applied in future maintenance activities.

Figures S10–12 of Supporting Information S1 and Table S5 of Supporting Information S2 show the total share and amount of traffic volume calculated for each traffic class and scenario, respectively.

2.3.4 | Predictive maintenance

Based on the estimated lifetimes (Table S3 of Supporting Information S2) and future traffic scenarios, it is possible to predict the probability of maintenance activities for the in-service roads. A probability density function was allocated to the roads belonging to a certain traffic class for each year to predict the proportion of area that would require maintenance in the following years.

Paved roads were clustered into seven traffic classes by considering the registered AADT in the year the maintenance activities were performed. To identify how many road sections would stay or change their traffic class before an intervention, it was essential to know when roads would change traffic class. In doing so, we followed each paved section based on its traffic class until the year that the area underneath the probability density function became greater than 99%. By adopting such an approach, it became possible to control the classification of roads based on the representative traffic classes. However, after the first maintenance activity comes follow-up maintenance activities to ensure that the in-service roads are at an acceptable service level. To make sure that the system would be maintained indefinitely, the areas of the roads that were maintained were added to the schedule for the next maintenance activities.

As several kilometers of roads were maintained before 2017, and they were still in service, it became necessary to incorporate the 99% approach to the retrospective study to estimate the probability of these roads being maintained until the end of 2017. This incorporation subsequently resulted in the necessity of implementing the three traffic scenarios, because we did not know how the traffic volume would be after the year 2017.

Among the different types of maintenance works, only milling and paving activities were considered. Milling was assumed to be carried out before paving, and paving was assumed to involve surfacing and binding layers. During maintenance work, some portions of the road surface[2] would be milled while some portions would require binding layers. However, the surface layer was assumed to be applied over the entire road surface during the maintenance work. To determine the amount and variability in paving and milling, this study used historical data that represented road paving and milling activities to estimate the depths of the surface layer, binding layer, and milling and the proportion of the binding layer and milling for different traffic classes (included as Tables S4 in Supporting Information S2). Also, we assumed that the lognormal distribution would explain the uncertain nature of the variables.

Similarly, the uncertainty in the calculated mass was determined based on a uniform distribution and 100 iterations. Equations to predict the maintenance activities can be found in Appendix S4 of Supporting Information S1.

2.3.5 | Dissipative flow

Wearing is a result of the interaction between tires and the road surfaces, which results in losses of materials. A combination of different factors, like tire type, angular speed, weather conditions, and surface type, can result in variations in the amount of wear due to a pavement surface. Here, the dissipative flows from the road infrastructure were limited to the surface wear from roads. In this study, it was assumed that wear is caused by passenger vehicles equipped with both studded tires and nonstudded tires (i.e., both winter and summer tires).

For the case of studded wear, the amount of wear gradually reduced over the years (by about 80% from 1970 to 2000). This reduction has been attributed to the introduction of pavements with higher wear resistances that produce less wear (Snilsberg, 2008). In this study, we applied the historical wear amounts for the years 1980–2050: 15–20 g/km/year for 1980–1989, 10–15 g/km/year for 1990–1999, and 5–10 g/km/year for 2000–2050. From 2000 onward, we assumed that the rate of wear remains constant until the end of the analysis period, as not much differences have been observed in recent years (B. Snilsberg, personal communication, April-May 2019). For the case of nonstudded wear, it was assumed that the wear is about 1/50th–1/60th of studded wear for different years (Snilsberg, 2008). A uniform distribution was considered for the probability of wear from nonstudded tires.

Similar to the changes in the rate of wear over the years, the share of vehicles equipped with studded tires has changed. The change has shown a downward trend in terms of the number of vehicles with studded tires, which has resulted in a reduction in the amounts of wear and particles formed per vehicle (NILU, 2019). Despite the decreasing trend in the use of studded tires, not enough historical data exists to properly reveal the changes over time. We extrapolated the records in both retrospective and prospective directions to show the shares of both tire types in Norway (Figure S5 of Supporting Information S1).

To create the extrapolated figure, the observed data, which show the percentages of nonstudded tires in different municipalities in different years, were weight averaged with respect to the total recorded AADT in each municipality for each year. In addition, it was assumed that all the vehicles used studded tires in 1950. Subsequently, the proportionate results in each year were fitted to the logistic distribution to depict the trend from 1980 to 2050. The used equations to quantify the mass of pavement wear through the analysis period can be found in Appendix S4 of Supporting Information S1.

[2] Here, by the term "road surface" we refer to the wearing course and binder course.

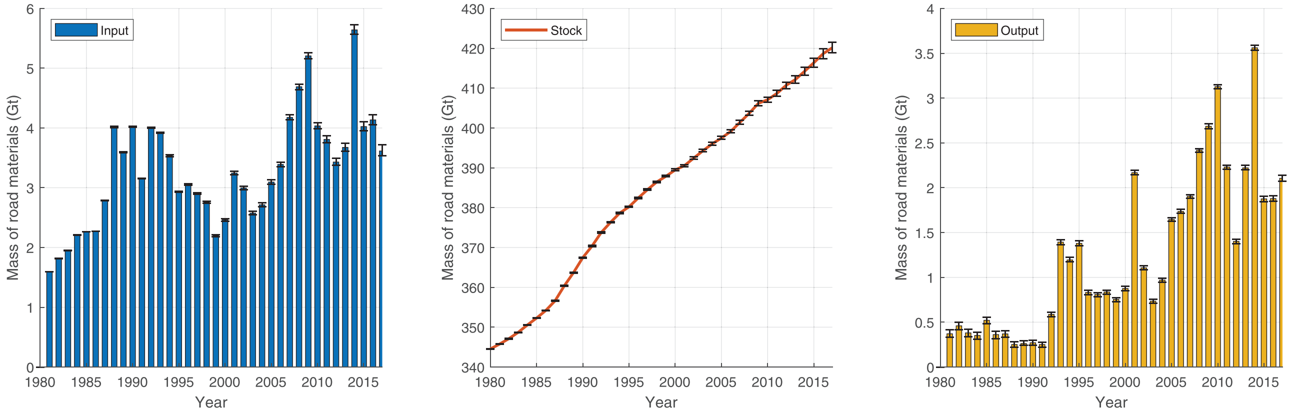

FIGURE 2 Retrospective results showing the stock and flow of road materials in Norway between 1980 and 2017. Underlying data for Figure 2 are available in a table entitled "Figure 2" of Supporting Information S2

2.4 | Retrospective analysis

To estimate the availabilities of road materials between 1980 and 2017, a retrospective approach was developed. The approach quantified the amount of in-use stock based on the inputs and outputs of the system. The estimate was based on four main variables: (1) road structure; (2) historical maintenance activities; (3) predictive maintenance activities; and (4) dissipative flow.

2.5 | Prospective analysis

To forecast the future materials flows and stocks in the road networks, a prospective approach was introduced. In this approach, the same road networks as those in 2017 would be in service until 2050, because it was assumed that there would be no changes within the system in terms of building or decommissioning the road structure. Nevertheless, the system would be maintained indefinitely to ensure its serviceability. Here, the analysis is based on two main variables: (1) predictive maintenance activities and (2) dissipative flow.

3 | RESULTS

3.1 | Retrospective findings

Figure 2 shows the changes in the number of inputs, outputs, and stocks from 1980 to 2017. It provides the overall changes within the system, and it shows the uncertainties in the results for each year in the form of vertical error bars that display the 10th and 90th percentiles of the random calculation.

The retrospective results presented in Figure 2 show the stocks and flows for the baseline scenario only. This was done because the intensity of road materials remain quite unchanged, regardless of the assumed traffic scenarios (see Figure S6 of Supporting Information S1). The reason for such tight similarities in the findings was that the projected paving and milling activities for the predictive maintenance activities were the only variables that differed among the others during 1980–2017 and exhibited minor differences (for more information see Figures S7–S8 and more details explained in Appendix S5, all in Supporting Information S1). The other variables were constant during the same period for the three scenarios.

By inspecting the historical changes in the number of road structures (see Figure 3a), it can be seen that more roads were built than decommissioned between 1981 and 2017. The infrastructural development showed that the net growth of the networks was about 18 GT during 1981–2017, due to investments in new road infrastructure. Over the retrospective period, about 45 GT of road structures (i.e., foundations including both bound and unbound layers) were added, while about 27 GT of road structures were removed. Similarly, records from the historical maintenance activities showed that overall, more road materials were added than removed (Figure 3b). During 1981–2017, about 68 GT of paving materials (i.e., wearing, and binder courses) were placed on roads during the maintenance activities, and about 13 GT were removed due to milling and decommissioning of road pavements and structures, respectively. It is worth mentioning, "estimated" values in Figure 3 refer to the output values from Sections 2.3.1 and 2.3.4 while "recorded" values refer to historical records that are not from modeling. In addition, "road structure" reflects on the structural composition of roads, while "road pavement" reflects on the pavement layers (i.e., here refers to the surface layer and binding layer).

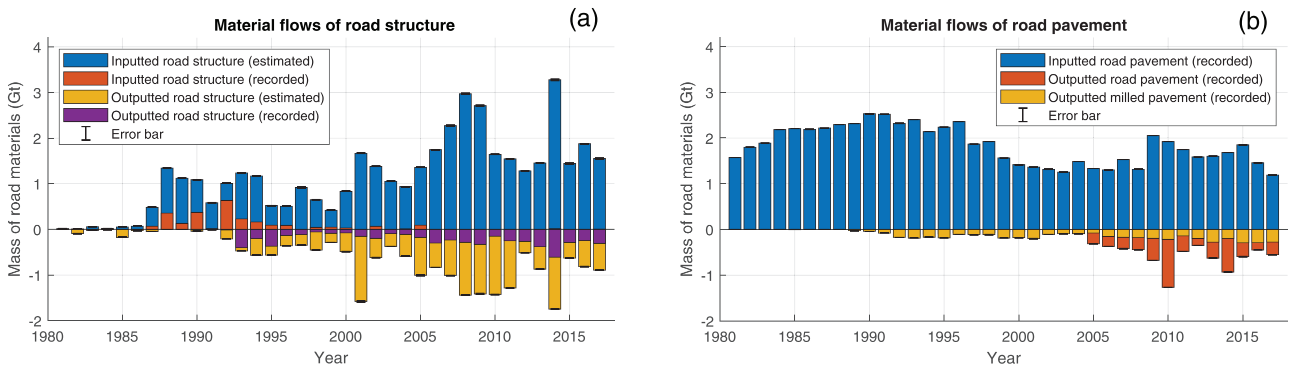

FIGURE 3 Material flows in and out of road structures and pavements between 1980 and 2017. Underlying data for Figure 3 are available in a table entitled "Figure 3" of Supporting Information S2

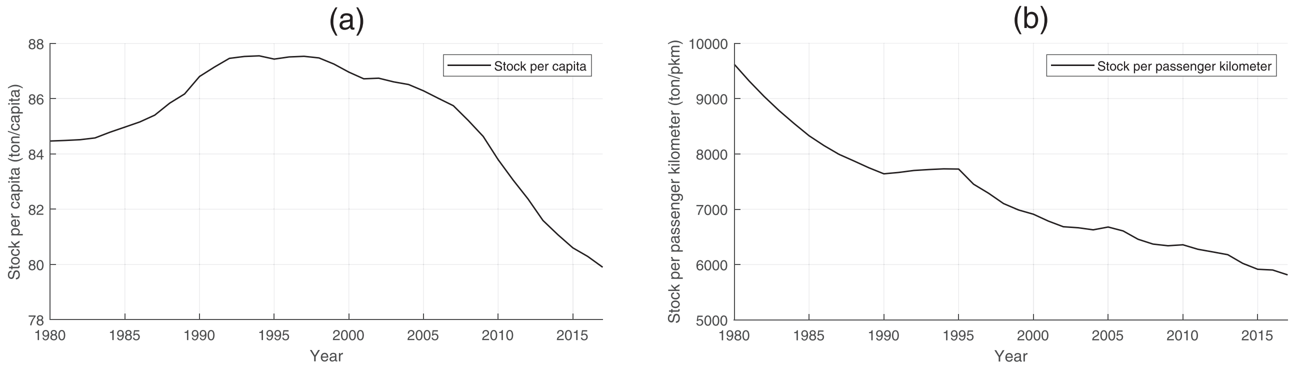

FIGURE 4 Stock per capita and per passenger kilometer (pkm) in Norway between 1980 and 2017 (*Source*: Statistics Norway (2020)). Underlying data for Figure 4 are available in a table entitled "Figure 4" of Supporting Information S2

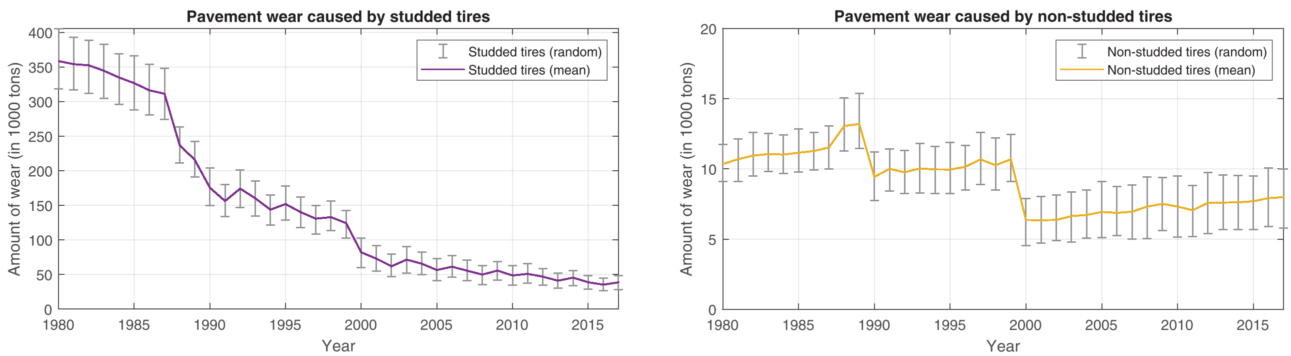

FIGURE 5 Pavement wear from 1980 to 2017. Underlying data for Figure 5 are available in a table entitled "Figure 5" of Supporting Information S2

Stock per capita and per passenger kilometer (pkm) has changed over time in Norway (see Figure 4a). The amount of stock per capita was at about 84 metric tons in 1980 and then slowly reached its highest during the 90s. However, the per cap stock reduced gradually from 2000, reaching the lowest ever in 2017 (almost 80 metric tons). Unlike the per capita stock, the amount of stock per passenger kilometer reduced over time; being nearly 9.6 kiloton in 1980 and becoming 5.8 kiloton in 2017. The per passenger kilometer stock reached remained unchanged during 1991–1995.

The estimated pavement wear caused by tires was the other input variable used to obtain the results of the retrospective analysis. Because the model presumed in the usage of winter tires showed a shift in share from studded to nonstudded tires (see Figure S5 of Supporting Information S1), a massive reduction in the amount of pavement wear caused by nonstudded tires is observed in the results. The reduction in the wear caused by studded tires was about 300 kT in the period 1980–2017 (see Figure 5). On the other hand, the reduction in the wear caused by nonstudded tires is not as significant as that caused by studded tires. As a result, even though the overall wear caused by nonstudded tires reduced after 2000, the wear gradually increases, as it was assumed that the market share of nonstudded tires would continue to increase.

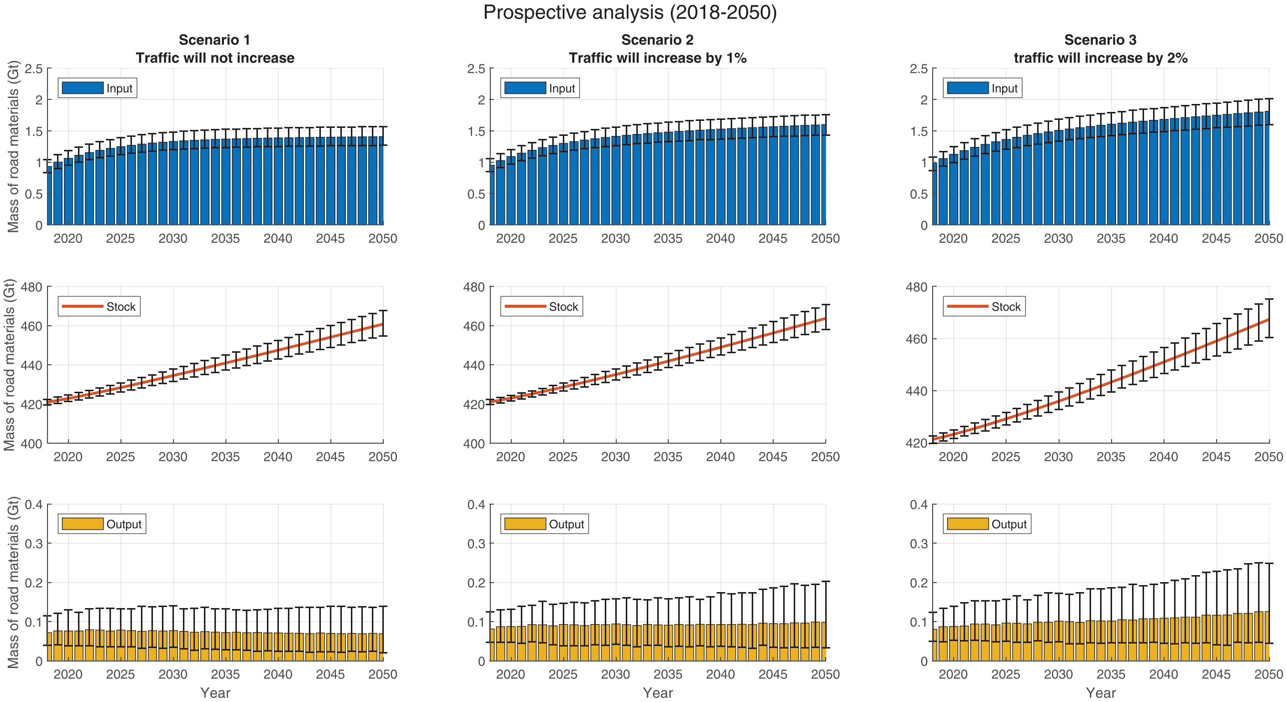

FIGURE 6 Prospective results showing the stock and flow of road materials between 2018 and 2050. Underlying data for Figure 6 are available in a table entitled "Figure 6" of Supporting Information S2

3.2 | Prospective findings

In the prospective analysis, the calculated results showed the changes in the system from 2018 to 2050 (Figure 6). Unlike the retrospective analysis, the results of the prospective analysis were not identical across the scenarios. Even though this analysis was based on three parts (i.e., projected paving, milling, and wear), the amount of stocks continued to grow over time (it was the highest for Scenario 3 and the lowest for Scenario 1). In addition to the higher share of inflows compared with that of outflows, the reclassification of roads from their initial traffic class to higher traffic classes was the reason for the increase in the maintenance frequency (Figure S9 of Supporting Information S1).

In Scenario 1, the overall traffic growth in each road section was limited to the period between 1980 and 2017 and revealed a steady state from 2018 to 2050. Even with no further changes in the traffic classes after 2017, some roads showed shifts in their initial traffic classes that resulted in an increase in the need for roads with lower maintenance lifetimes. However, the divergence appeared to be more pronounced for Scenarios 2 and 3. In these two scenarios, the roads in lower traffic classes shifted to higher traffic classes more actively and continuously.

The future pavement wear shows that, under the three traffic scenarios, the pavement wear caused by studded tires continued to decrease owing to the continuous reduction in their share (Figure 7). The highest reduction in the pavement wear caused by studded tires was for Scenario 1 and the lowest reduction was for Scenario 3. This was found to be related to the effect of traffic volume in each road section throughout the period 2018–2050 (a higher percentage of growth in the annual traffic volume resulted in a relatively lower reduction in the pavement wear caused by studded tires).

On the other hand, the pavement wear caused by nonstudded tires showed the opposite trend. Owing to an increase in the number of nonstudded tires, the pavement wear increased in the period 2018–2050. The growth was insignificant for Scenario 1 but Scenarios 2 and 3 showed more significant increases in the amounts of pavement wear.

4 | DISCUSSION

The material stock per capita in Norway was estimated to be about 80 metric tons in 2017, which is relatively high compared to prior MFA works (Guo et al., 2014, 2017; Han et al., 2018; Miatto et al., 2017; Tanikawa & Hashimoto, 2010; Tanikawa et al., 2015; Wiedenhofer et al., 2015). Such a higher material stock per capita was partly explained by the differences in the population density between the studied cases. Studies that involved fewer inhabitants per square kilometer displayed higher material stocks for road infrastructure. In addition to the population density, there were systematic differences between the cases, for example, in the coverage of different road infrastructures, inclusion/exclusion of different materials,

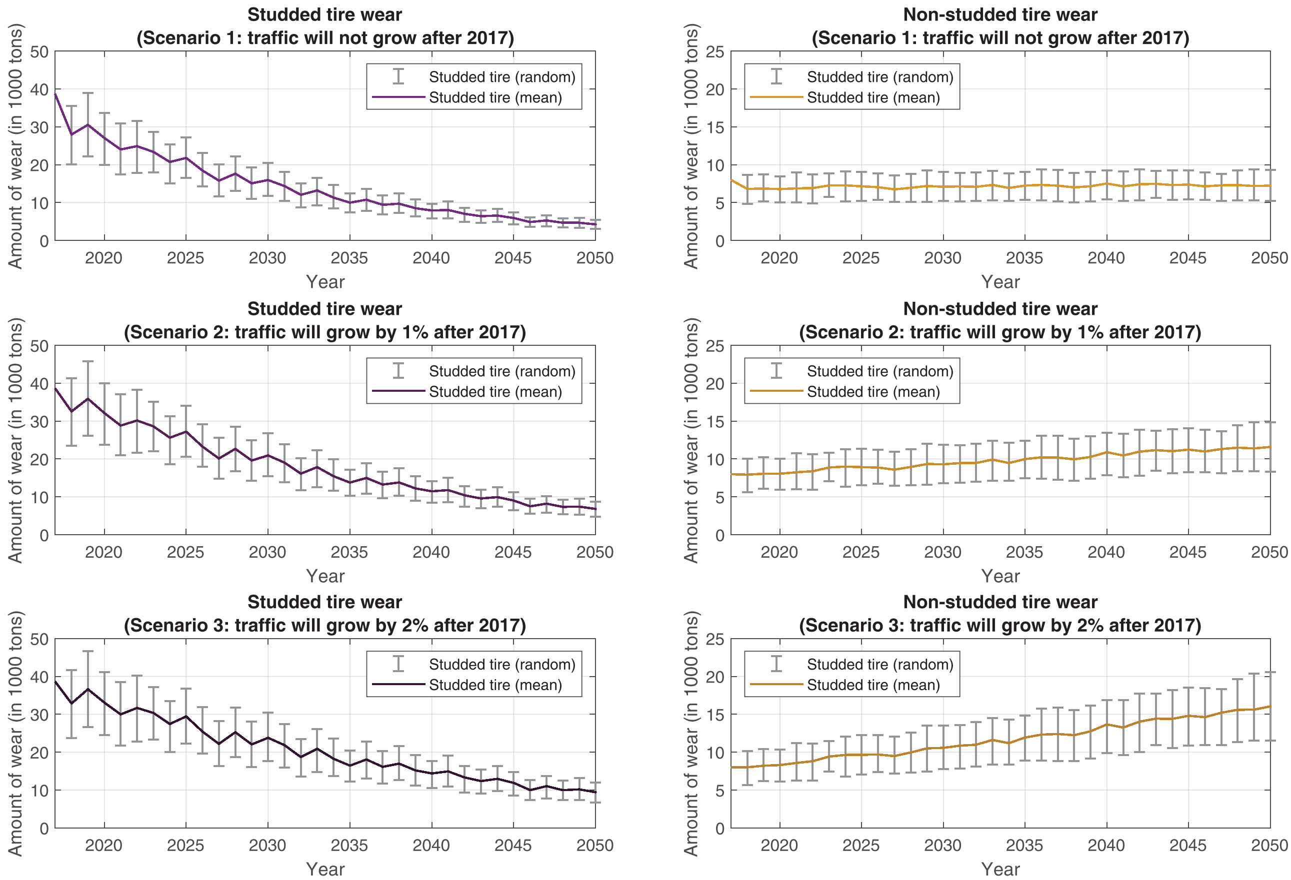

FIGURE 7 Pavement wear from 2018 to 2050 for the three scenarios. Underlying data for Figure 7 are available in a table entitled "Figure 7" of Supporting Information S2

and usage of different material intensity factors. Appendix S6 of Supporting Information S1 compares the obtained results from this study with a few other road MFA works.

The prospective analysis showed the transition in the road material demand after the year 2017 based on three scenarios. By knowing the in-service stocks in 2017, and estimating the exogenous lifetimes and wear coupled with randomized mass densities, it became possible to show the stocks and flows of the road materials until 2050. Even though the presented results were limited to the maintenance activities and pavement wear, the outcomes of the analysis can be useful for decision-makers to consider initiatives and strategies geared toward the sustainability of the road infrastructure.

Utilization of the discussed iterative ML model and incorporation of sensitivity analyses made it possible to overcome limitations in prior research, which used a fixed structural (i.e., theoretical) design for different categories of roads in the networks. The introduced ML model in our study made it possible to synthetically design road structure based on external factors and avoid creating archetypes. In the archetype-based approach, one can easily get trapped in an exhaustive process due to the exponential growth in covering various options (e.g., traffic volume, subgrade types, and many more). The core purpose of using the iterative ML models was to show the opportunity of using an alternative approach that can overcome the very demanding part of the archetypal mapping (creating representative infrastructure sets to depict a cluster of road infrastructure).

Conducing the traditional archetypal model and comparing its results with the ML models were beyond the limit of this paper. However, based on our earlier work using the traditional archetypal model (Gontia et al., 2019), the benefits and drawbacks of using the introduced ML-based model compared to the traditional archetypical approach can be expressed as follows:

- Correct representation of different road clusters is time demanding in traditional archetypical models: As modeling individual road sections in a network requires detailed information, the traditional archetypical approach to model roads has become popular as similar roads can be modeled with available information. However, the limitation of such an approach is the correctness of the used delimitator to correctly cluster different roads. As roads can be clustered with different determining variables (like traffic volume, pavement material types, and a number of lanes), correct selection of variables to cluster different roads is essential to avoid oversimplification. Given the generic nature of the archetype composition, it holds uncertainties within the selected variables to represent road archetypes. If one tries to create archetypes with distinct characteristics to reduce uncertainties (and to avoid oversimplification of archetypical approach), many hours can be easily spent to capture the flexibility of different road clusters.

- Supervised learning here required sufficient and reliable input data: The introduced supervised learning in this study utilized historical data on the road structure containing layer compositions and thicknesses of many point data. These data provide sufficient input to both train and test the ML models. However, without having such historical data, conducting the supervised ML using similar ML models would have been difficult. Such limitation eventually tails to another challenge connected to the selection of ML models. The selection of correct ML models is a prerequisite to satisfy an ML task. Understanding how different ML works, especially with concern to supervised learning, is essential to make informed decisions.

Although there are other possible ML models, the classified and regression tree models showed considerably faster execution speed. Table S2 of Supporting Information S2 shows the faster execution speed by the decision tree models compared with the linear regression models and the support vector machines. Besides having a faster execution speed, the used decision tree models showed relatively more accurate testing results compared to those of the others. Even though attaining a relatively high accurate prediction in a supervised learning model is heavily dependent on the quality and the number of data points, Table S2 shows that across the models, the decision tree models could result in more accurate outcomes.

The use of uncertainty analyses (i.e., in forms of randomized and iterative ML, predictive maintenance activities, and material intensities) to estimate and predict stocks and flows in retrospective and prospective analyses, respectively, made it possible to reveal the magnitudes of the deviations from the means in the results. These deviations were shown via error bars in the stocks and flows figures that represented the upper and lower bounds of the deviations from the mean.

The integrated uncertainty assessment helped go beyond the streamlined MFA modeling approach (often using fixed values) to show a probabilistic figure of estimation and prediction of material flows and stocks. The inclusion of uncertainty analyses also showed the propagation of possible error caused by parameter uncertainties in the system and presented how the domain of induced uncertainties propagates as time advances. The ranges of the deviations were observed to be greater for the predictive maintenance activities and dissipative flow, compared to those for the road structure and historical maintenance activities. The reason for such behavior was found to be related to a wider range of deviations in the statistical data (Tables S4 in Supporting Information S2) for paving and milling activities (i.e., Figure 6 and Figures S8 and S9 in Supporting Information S1).

The inclusion of dissipative flows due to tire–pavement interaction bridged the existing gap in the MFA of road infrastructure and showed the intensity of the material loss over the period of assessment. The magnitude of material loss compared to the total annual outflows had an infinitesimally small contribution (i.e., relative mass). Over the studied period, the share of the loss of materials from the tire–pavement interaction did not exceed 0.9%. Even though the relative share is very small, the human health issues of particle formations caused by the abraded road surface is a concerning issue discussed for years, especially in cold climates (Kupiainen et al., 2017).

Even though it was assumed that the networks would not change after 2017, the results from the maintenance activities showed that more materials were placed than removed (i.e., accumulation of road materials caused by putting more paving materials on the roads than removing them). Such behavior is in line with the information presented in retrospective results from Figure 2. As shown, a higher mass of paving materials was placed than milled. However, it is important to consider that height restrictions (how thick a road pavement can get) in various road sections make it difficult to continuously add new paving materials without removing them. This restriction can be imposed as it may impact road standards and regulations (like road clearance, ride comfort, and drainage system), and subsequently puts lives in danger (NPRA, 2014). More explanation is provided in Appendix S6 of Supporting Information S1.

Although the fate of milled paving materials along with those of other outputs was not evaluated in this study, the outflows from the road networks seldom exit the transport infrastructure system. Instead, they are typically reused in new pavements or other applications (KFA, 2018). It is essential to expand the research to gain a deeper understanding of the rate of up/downcycling in the Norwegian road networks and apply various scenarios to reveal alternative pathways that promote sustainable use of road materials.

4.1 | Limitations

Reliability of the presented results in this investigation is heavily dependent on the correctness of the data and models used. The introduced uncertainties (by means of random sampling) have tried to show the probability of the correctness in the applied method. However, because different assumptions have been made along the study and the iteration was limited to 100 rounds of random sampling, we would like to advise that the presented results be used only for the illustration of the method and not for any decision-making.

Even though it is not uncommon to see a growth in the expansion of road networks, this study did not consider that the networks would expand or shrink after 2017. Instead, it was assumed that the networks would only be maintained. In future research, it would be valuable to expand this work and consider scenarios (reinforced by uncertainty analysis) involving the combination of network expansion and maintenance activities.

Often, owing to new requirements and technological advancements, the structural design of road infrastructure is modified. Such modifications are introduced to increase the performance and durability of road infrastructure while maintaining high safety and comfort. In our study, however, no distinction was made to differentiate between road structures in different cohorts. This shortcoming was because of not having first-hand data for road structure in different cohorts.

The Weibull distributions used to explain the distributional lifetimes of the different traffic classes did not distinguish between different road materials. As there are different road materials within a traffic class, it would have been necessary to make such a distinction. However, this was not considered, as there was no information suggesting what types of road materials would be laid as part of the next intervention activities.

The clustering approach that roads would maintain or change their traffic classes was arbitrary and did not offer the flexibility of shifting the road traffic classes at that point in time when they would change to a new traffic class. Instead, it considered the traffic volume during the year when more than 99% would be maintained to decide how many (in percentage) would stay in the current traffic class or shift to other traffic classes. Although the applied approach might not significantly impact roads with higher traffic volumes, as they display shorter distributional lifetimes, the subjectivity of the considered approach might affect roads with lower traffic volumes (owing to their longer distributional lifetimes).

One potential threat in the introduced ML model was left unsolved. The idea of predicting one layer at a time and then using the outcomes to predict the next layer could potentially result in induced errors in the estimated road structure. This challenge happens when the model makes wrong prediction for a layer that belongs to a road section, and then predicts the remaining layers of the road section based on incorrect inputs. Unfortunately, this is an area that the introduced supervised learning method in our study is unable to resolve, which may subsequently result in wrong estimation of material intensity in the studied road networks.

Appendix S7 of Supporting Information S1 covers some other limitations that were not discussed in this subsection.

5 | CONCLUSION

The proposed method presented a potential approach to quantify the material stocks and flows in a dynamic system by using the Norwegian case to showcase its findings. It revealed the material stocks and flows from the past to the future by measuring the dissipative flow and uncertainties to close some of the gaps identified in prior research.

The study developed its method by means of classification and regression trees to close the gaps commonly found in MFA studies due to using archetypical mapping of road infrastructure. It presented a potential method to estimate road material lifetimes and apply the findings to predict maintenance activities. The dissipation of road materials due to tire–pavement interaction was also assessed to reveal the amount of material lost from the system that cannot be recycled or reused. It also proposed three traffic scenarios to project future changes in the traffic volumes.

This study introduced a potential approach to quantify the pavement wear caused by tire–pavement interaction. It showed how much mass from roads would be dissipated, which is not recoverable. This quantification was important as there have been few attempts at revealing the dissipative flows for the road infrastructure through MFA research. In addition, our method would help quantify abrasion from the road network in a justifiable effort, which may assist in increasing the resolution from national accounts of material flows (Eurostat, 2018). However, further research should be conducted to add more detail to the developed method, such as the effects of surfacing type, aggregate nominal maximum size, speed limit, and climatic conditions on pavement wear.

In future research, it would be beneficial to expand the system boundary by including infrastructures such as tunnels, bridges, dwellings, and sewage systems. The inclusion of other physical infrastructures will provide a platform to assess the possibility of material exchange between the different infrastructures due to the generation of different wastes from demolished structures. It would also be worthwhile to couple the findings with other life cycle-based methodologies (e.g., life cycle assessment, life cycle costing, and social life cycle assessment) to extend the approach that is traditionally employed in MFA analyses (assessing the availability of secondary materials in terms of quantities and time and evaluating their potential to theoretically substitute virgin materials) to include other related dimensions (e.g., environment, economy, and society).

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the Norwegian Road Databank. Restrictions apply to the availability of these data, which were used under license for this study. Access to the data used in this study is possible only if one makes an agreement with the Norwegian Public Road Administration directly.

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SUPPORTING INFORMATION

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