A novel LUTI model calibration using differential evolution algorithm

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ABSTRACT LUTI (Land-Use and Transportation Interaction) models are decision-making aid tools that simulate complex dynamic bilateral feedback between transportation and land-use models within a territory. Although calibration (parameter estimation) is a crucial requirement of LUTI models, fully automated approaches with the usage of multi-objective functions have not been fully addressed. To address this limitation, a generic calibration approach is proposed for the parameters of the land-use model using a differential evolution algorithm. A global sensitivity analysis was performed to identify the most important land-use model parameters. These parameters were then calibrated using the differential evolution algorithm with the Root Mean Square Error (RMSE) and Mean Absolute Normalized Error (MANE) as multi-objective functions. Five key capabilities are provided in the suggested technique for calibration of LUTI models including 1) global estimation rather than local estimation, 2) consideration of multi-objective functions, 3) continuously improving the results, 4) easily adaptability, and 5) involving multi parameters in the calibration process. The TRANUS land-use model was used to test the performance of the suggested calibration technique. The validation and consolidation of the approach were tested based on convergence, minimization of errors, and modeled/observed data ratio by comparing with the genetic algorithm and particle swarm optimization techniques. The suggested approach using a differential evolution algorithm outperformed both genetic and particle swarm optimization techniques and provided the most stable and diverse solutions.

INDEX TERMS Differential Evolution; Multi-objective Optimization; Calibration; LUTI; Land-Use; Transport Modelling; TRANUS.

I. INTRODUCTION
Land-use and transportation interaction are fundamental concepts in the study of land development and the formulation of transport links [1]. Land-use and transportation planning have been done separately in most scenarios, which means that the impact of any changes in transportation policies on the land-use patterns is frequently ignored. Urban sprawl is one of the consequences that occur due to ignoring such bilateral impacts in the planning process [2].

LUTI (Land-Use and Transportation Interaction) models are designed to predict the interrelations between economic growth and transport demand and vice versa (for more information see [2]). These interrelationships between transportation systems and land-use activities are shown in Fig. 1 and Fig. 2.

LUTI models have been used to examine the impact of transport and land-use policies such as the implementation of transportation infrastructures (e.g., highway development, underground systems), dwelling and business improvements, improvement of public transport and fare changes, the expenses of private transport, and the development of socio-demographic and economic scenarios as well [3]. Calibration (parameter estimation) is the most crucial factor in LUTI models [4]. This refers to the estimation and adjustment of model parameters using a numerical method to minimize discrepancies between actual and modeled data. However, econometric ad-hoc procedures and trial and errors techniques have been conventionally used to calibrate LUTI models [5]. Abraham and Hunt [6] developed a semi-automatic calibration approach for MEPLAN based on the least square optimization technique. They proposed a simultaneous and sequential calibration approach that was later used in the location choice model for nested logit parameters. PECASE LUTI model was also calibrated using the minimization of the least square technique [7].

Dutta et al. [8] developed an algorithm to calibrate the LUTI models using maximum likelihood estimation. Furthermore, they examined the propagation of uncertainty during the calibration process of TRANUS using the Monte Carlo method. Then, a probabilistic verification methodology of the calibration process using a statistical hypothesis test was proposed [8]. They noted that the error in the observed values...
of the outputs from the land-use module follows a Gaussian error.

prices may not be performed automatically and requires an expert eye. Later, Feudo et al. [13] proposed a semi-automatic process using non-linear optimization and curve fitting to calibrate the floor space substation parameters. They also extended the technique proposed by Capelle et al. [14].

Gilquin et al. [5] proposed a LUTI model calibration procedure consisting of a global sensitivity analysis to select the most influential parameters of the TRANUS model and an iterative optimization combining stochastic and deterministic approaches. They concluded that their proposed technique outperformed a former ad-hoc calibration procedure in terms of variance and maximum of the normalized adjustment parameters (shadow prices) by reducing the value of the variance by a large margin with a drastic gain of time.

Particle Swarm Optimization (PSO) was used by Boittin et al. [15] for the calibration of LUTI models to overcome the limitations of existing methods. They came to the conclusion that many PSO variants are emerging and it is not yet clear which one offers better calibration results.

Most of the existing LUTI calibration techniques are semi-automated, using single-objective functions, local estimation techniques, and suffer because of the lack of a global estimation process. An automatic and global calibration approach is a highly desirable goal in this sense, and the studies mentioned have already made effective steps to this end. Developing an automatic and global estimation approach for the calibration of LUTI models using a multi-objective optimization technique is aimed by this study. To do so, the Differential Evolution (DE) algorithm, one of the most powerful Evolutionary Algorithms (EAs), has been selected as an optimization tool. DE was used because of its simplicity in terms of programming, fast convergence, global estimation, and the ability to find optimum solutions almost in every iteration. The land-use and activity model of TRANUS (one of the well-known open-source LUTI models) has been selected to test the suggested calibration technique. Then, the performance of the suggested techniques has been compared to the two other EAs namely Genetic Algorithm (GA) and PSO.

Further sections of the article deal with the following: In Section 2, the theoretical basis of TRANUS calibration and the sensitivity analysis process are presented, while section 3 explains the suggested calibration technique, which is followed by the results of the study and discussion in Section 4. Lastly, in Section 5 the research findings are concluded and highlighted, and some proposals for further studies are offered.

II. TRANUS LUTI model

A. THEORETICAL BASIS OF TRANUS SOFTWARE

TRANUS [16] is a macroeconomic equilibrium type model, which combines two modules: (1) land-use and activity module; to simulates a spatial economic system by analyzing activity locations and economic sectors relationships, and (2)
transportation module: to calculate the usage of the transportation network as well as the related disutility.

Random utility theory was used by both modules of the TRANUS e.g., discrete choice logit models for designation of activities and land-use such as activity-location, land-choice, multi-modal path choice, and assignment. The modules are then run iteratively till production and consumption demands for each area are met and equilibrium is achieved [17]. A set of adjustment parameters (called shadow prices) that assist the model to attain a better response and a more precise match to the observed data are computed by the TRANUS. Mathematical descriptions and details of the TRANUS model can be found here [18].

B. SENSITIVITY ANALYSIS OF TRANUS LAND-USE AND ACTIVITY MODEL PARAMETERS

Sensitivity analysis determines how variation in the output of a numerical model can be attributed to variations of its input. Assessing the sensitivity of the input parameters on the outputs is a crucial step to reach a proper calibration of the model and ensure better predicting capabilities. Global sensitivity analysis was used for a range of very diverse purposes, such as supporting model calibration, verification, diagnostic evaluation [19], [20], to prioritize efforts for uncertainty reduction [21], to analyze the dominant controls of a system [22], and to support robust decision-making [23].

Sobol [24] established a variance-based method for calculating sensitivity indices termed Sobol’ indices, which is one of the many approaches available. The influence of each input or set of inputs is represented by these indices, which range between 0 and 1, – with the higher the index, the more influential the input.

Higher-order indices estimate the equivalent relevance of interactions between inputs, while first-order indices estimate the principal influence from each input. Various estimating methodologies have been utilized in the literature [25] to estimate Sobol indices. A sensitivity analysis has conducted using generalized Sobol indices on the land-use and activity module parameters of the TRANUS, which are presented in Table 1.

| TABLE 1. Parameters that are assumed unknown |
|---------------------------------------------|
| Parameters | Description |
| δmn | elasticity parameter of the sector (m) concerning the error of sector (n) |
| bkn | the relative weight of sector (k) as an attractor to the sector (n) |
| fn | dispersion parameter of multinomial logit model for sector (n) |
| Wj | the initial attractor of the zone (j) considering non-modeled elements that attract the location of the sector (n) |
| Atrac.Facn | attractor factor respect to sector (n) |
| λn | the factor that regulates the relative importance of prices versus transport disutility in the utility function related to the sector (n) |

To apply the sensitivity analysis, TRANUS model was firstly coded using Python. Then, the generalized Sobol indices for land-use and activity module parameters that were assumed unknown were estimated using an open-source Python library known as SALIB [26]. In this process, Mean Absolute Normalized Error (MANE) has been used as error function, and the influences of input values (parameters given in Table 1) on the MANE values of the productions (Xn) and prices (Pn) that act as the TRANUS model output were calculated. The MANE formula is given below:

$$\text{Output}_{\text{MANE}} = \text{MANE}_X + \text{MANE}_P = \frac{1}{N} \sum_1^n \frac{|X_{\text{act}} - X_{\text{mod}}|}{|X_{\text{act}}|} + \frac{1}{N} \sum_1^n \frac{|P_{\text{act}} - P_{\text{mod}}|}{|P_{\text{act}}|}$$

Whereas Xact and Pact are observed productions and prices, Xmod and Pmod are modeled productions and prices, N is the number of observations, and OutputMANE acts as the model overall output against input parameters. The Sensitivity analysis was carried out on five sets of TRANUS model parameters, and the results are shown in Fig. 3 and Fig. 4.

As seen in Fig. 3, and Fig. 4, the highest impact on the model output (OutputMANE) is resulted by λn (price factor) and δmn (elasticity). That is why these two parameters were selected to be used in the calibration process.

III. LUTI calibration technique incorporating DE Algorithm

EAs attempt to imitate the natural evolution rules of the biological world and they share several common processes as
follows: (1) the initial population of individuals (solution potentials) is generated randomly, (2) individuals are evaluated for fitness value (how close is individual to the objective function), (3) solutions are selected based on each individual's fitness value, and (4) a new population is generated through the perturbation of the solutions selected [27]. Gradient knowledge is not required by evaluation algorithms, a sample of a population is used to determine the optimum solution instead. EAs have been extensively used for calibration and optimization, the most popular ones being GA[28], PSO[29], which are considered similar to our suggested calibration technique using the DE [30] algorithm.

In various research investigations and model evaluations, Root Mean Square Error (RMSE) and Mean Absolute Normalized Error (MANE) have been employed as standard statistical metrics to measure the goodness of the proposed models. Even though they have been used to evaluate model performance for many years, there is no agreement on which metric is the best appropriate for model errors [31]. Both RMSE and MANE were used in this study as a measure of the goodness of the suggested calibration technique.

A. GENETIC ALGORITHM

GA [28] is one of the most well-known optimization algorithms based on natural processes that occur in the environment, and it considers Darwin's theory of species evolution. In GA, there is a randomly selected population of individuals/candidates, which might be a possible solution to the problem. The solutions are evaluated using the fitness function value of each candidate which is a particular type of objective function. Fitness function value has been used to show how a solution is good enough in reaching to the set aims. GAs have three common operators; (1) selection (selects parents randomly from initial population for the reproduction process, based on their fitness value), (2) crossover (combines parents to produce new offspring (children), with single, double, or uniform crossover techniques), and (3) mutation (modifies individuals/gens which are selected based on mutation probability). GAs are suitable for discrete and noisy spaces to find the optimal design solution [32]–[34]. Complex circumstances, such as nonlinearity and shifting parameters, impose increased demands on the use of GA in land-use research with infinite issues [35]. Although several GA versions have been developed so far, the GA version coded by Kamel [36] was used in this study. GA design is limited to maintaining the balance between crossover and mutation rates [37], thus crossover probability (crosso) and mutation rates (mu) were tested over the range (0 to 1), and the best combinations were selected through a trial-error process for RMSE and MANE, as presented in Table 2.

| Parameters | Description |
|------------|-------------|
| npop = 30  | initial population number |
| c1 = 1.5   | personal acceleration coefficient |
| c2 = 1.3   | global acceleration coefficient |
| w = 0.9    | inertia weight |

TABLE 2. Parameters selected for GA operators (RMSE and MANE)

| Parameters | Description |
|------------|-------------|
| maxit = 1000 | maximum number of generations |
| nPop = 30   | initial population number |
| crosso = 1  | crossover probability |

B. PARTICLE SWARM OPTIMIZATION

PSO is a population-based algorithm that was first introduced by Kennedy [29]. Two elements are required in PSO namely search space (a swarm of particles) and particles (potential solutions). As in GA, PSO also starts with initialization, where particle swarm will be generated randomly based on defined parameters, and proceeds by calculating the objective function depending on the position and velocity of each member (particle). Then, the objective function values are compared to the global objective function values to see which is superior. The best particle information is used to compute the new particle velocity and location. The fundamental benefit of PSO is that at every iteration, information is flowing between all particles. This means that all particles rely on other data to arrive at the optimal answer. Although several PSO versions are available, the one coded by Kamel [36] was used in this study. To get the best set of the parameters for PSO optimization, acceleration constants (c1 and c2) and inertia weight (w) were tested over the range of (1 to 2) and (0 to 1) respectively, and the best combinations were selected through the trial-error process for RMSE, and MANE as presented in Table 3.

| Parameters | Description |
|------------|-------------|
| maxit = 1000 | maximum number of generations |
| nPop = 30   | initial population number |
| c1 = 1.5    | personal acceleration coefficient |
| c2 = 1.3    | global acceleration coefficient |
| w = 0.9     | inertia weight |

TABLE 3. Parameters selected for PSO operators (RMSE and MANE)

C. DIFFERENTIAL EVOLUTION

DE algorithms are another type of evolutionary method was developed by Storn and Price [30]. Like GA, the DE algorithm also has similar operators; namely crossover, mutation, and selection. The main difference between the GA and DE is the mutation scheme that makes DE self-adaptive selection process. Accessibility, efficient memory use, reduced computational complexity (it scales better when dealing with big issues), and less reliance on computing efforts (faster convergence) are the primary advantages of DE over a typical GA algorithm [38]. Moreover, DE optimization has several advantages: It is simple, fast, easy to use, very easily adaptable for integer and discrete optimization, quite effective in nonlinear constraint optimization, including penalty functions, and useful for optimizing multi-modal search spaces, as well as multi-models, multi-objective, constrained, and dynamic models [27], [39], [40]. DE algorithms outperform Adaptive Simulated Annealing, the Annealed Nelder and Mead approach, GA, the Breeder GA, the easy evolution strategy, and method of stochastic differential equations, as well as PSO algorithms, in terms of the number of function evaluations required for locating a
global minimum of the test functions [27], [30], [41], [42]. As a result, the DE algorithm is considered a global optimization tool to achieve the objective of this study.

The purpose of the calibration is to adjust the model set of parameters (here: price factor, elasticity, and shadow prices) that minimizes the difference between observed and modeled variables. In this study, these variables are productions $X_{nj}$ (indicates items from each economic sector n that are in zone j) and prices $P_{ij}$ (represent the costs of items of sectors n produced in zone j). Two multi-objective (prices and productions) functions namely f3 and f6 (that are linearly scalarized functions) have been used in this study described as follows:

\[ f_3(x) = \text{RMSE}_X = \sqrt{\frac{\sum (X_{\text{act}} - X_{\text{mod}})^2}{N}} \] (2)
\[ f_6(x) = \text{RMSE}_P = \sqrt{\frac{\sum (P_{\text{act}} - P_{\text{mod}})^2}{N}} \] (3)
\[ f_7(x) = \text{RMSE}_X + \text{RMSE}_P \] (4)
\[ f_8(x) = \text{MANE}_X = \frac{1}{N} \sum_{i=1}^{N} |X_{\text{act}} - X_{\text{mod}}| \] (5)
\[ f_9(x) = \text{MANE}_P = \frac{1}{N} \sum_{i=1}^{N} |P_{\text{act}} - P_{\text{mod}}| \] (6)
\[ f_{10}(x) = \text{MANE}_X + \text{MANE}_P \] (7)

Where $X_{\text{act}}$ and $P_{\text{act}}$ are observed productions and prices, $X_{\text{mod}}$ and $P_{\text{mod}}$ are modeled productions and prices, $N$ presents the number of observations, and $f(x)$ acts as the objective function. Pseudocode of the DE algorithm, which was obtained from [43] and was adapted for the LUTI model calibration purposes is shown in Algorithm 1. This algorithm consists of two main parts: namely initialization and the main loop. In the initialization part, the objective function and DE parameters’ values were defined, then a random initial population was generated. Furthermore, TRANUS model was run and the objective function for each member of the population was determined to obtain the optimal objective function value and its matching population. Then, in the main loop, for each member of the population in every iteration, the TRANUS model was run to evaluate the objective function (or cost function). The DE variations can be distinguished by different mutation and crossover schemes. The best set of DE parameters (mutation factor, crossover probability, and pop size) must be selected to get the best solution for a specific optimization problem. The following mutation schemas was tested with the mutation factor ($\mu_1(F1)$, $\mu_2(F2)$) and cross point probabilities (cros) in the range of (0 to 1). Through a trial-and-error process the best combinations were selected for RMSE and MANE, as presented in Table 5. In the following formula, k marks the current population member, while G represents the number of generations.

**Algorithm 1. Calibration of land-use model parameters using DE algorithm.**

**Initialization**
- Assign Objective Function
- Generate a random initial population $\{x_i\} i = 1, 2, ..., Np$
- Evaluate Objective function, $fitness = \{f(x_i)\} i = 1, 2, ..., Np % RUN TRANUS$
- $bestIndex = \text{arg min} (fitness)$

**Main Loop**
- For $i$ in range (G):
- For $j$ in range (Np):
  - For k in range (Np):
    - Select randomly
      - $x_{r1,G} \in [1;Np, replace = False]$
      - $x_{r2,G} \in [x_{r1,G} - \mu_1(F1) \cdot x_{r3,G} \cdot x_{r5,G}]$
      - $x_{r3,G} \in [0;1]$
      - $x_{r4,G} \in [x_{r2,G} - \mu_2(F2) \cdot x_{r3,G}]$
    - If $C_{rand[0,1]} < \mu_{CR}$
      - $u_{i,G} = v_{i,G}$
    - Else
      - $u_{i,G} = x_{i,G}$
  - End For
- Evaluate objective function, $fitness = \{f(u_{i,G})\} i = 1, 2, ..., Np % RUN TRANUS$
- Selection

**Evaluation of the objective function**


table 4. Parameters selected for DE operators (RMSE and MANE)

| Schema | Mutation functions (donor vector) |
|--------|----------------------------------|
| Sch#1  | $v_{i,(k,G)}=x_{(r1,G)}+\mu_1(F)(x_{(r2,G)}-x_{(r3,G)})$ |
| Sch#2  | $v_{i,(k,G)}=x_{(r1,G)}+\mu_1(F)(x_{(r2,G)}-x_{(r3,G)})+\mu_2(F2)(x_{(r4,G)}-x_{(r5,G)})$ |
| Sch#3  | $v_{i,(k,G)}=x_{(best,G)}+\mu_1(F)(x_{(r2,G)}-x_{(r3,G)})$ |
| Sch#4  | $v_{i,(k,G)}=x_{(best,G)}+\mu_2(F1)(x_{(r2,G)}-x_{(r3,G)})+\mu_2(F2)(x_{(r4,G)}-x_{(r5,G)})$ |
| Sch#5  | $v_{i,(k,G)}=x_{(r1,G)}+\mu_2(F)(x_{(r2,G)}-x_{(r3,G)})+\mu_2(F2)(x_{(best,G)}-x_{(r1,G)})$ |

**After testing above mentioned mutation schemas, the best results for this example were given by sch#2 alongside the parameters presented in Table 5.**

| Table 5. Parameters selected for DE operators (RMSE and MANE) |
|-------------------------------------------------------------|
| Parameters | PARAMETERS (MANE) | Description |
|-----------|-------------------|-------------|
| maxit = 1000 | maxit = 400 | maximum number of generations |
| npop = 30 | npop = 20 | initial population number |
| $\mu_1(F1)$ = 0.3 | $\mu_1(F1)$ = 0.2 | mutation factor |
| $\mu_2(F2)$ = 0.3 | $\mu_2(F2)$ = 0.2 | mutation factor |
| cros = 0.9 | cros = 0.8 | crossover probability |

Although lower and upper bound values of each parameter were generally used to clip mutated values, the values for each parameter obtained in the mutation process were evaluated with the upper and lower bounds of the desired parameters (shadow prices, lambda, and elasticity). If the mutation value obtained was out of the bound, the value of the current population was replaced as the mutant value.
\[
\begin{align*}
\text{If} & \quad f(u_{j,c}) < f(x_{j,c}), \\
& \quad x_{j,c} = u_{j,c} \\
\text{if} & \quad f(x_{j,c}) = f(u_{j,c}) \\
\text{if} & \quad f(u_{j,c}) < f(x_{\text{best},c}) \\
& \quad \text{bestindex} = j \\
& \quad x_{\text{best},c} = u_{j,c}
\end{align*}
\]

End If

End If

If the repetition of \( f(x_{\text{best},c}) = 40 \) OR \( (f(x_{\text{best},c}) - \text{AVE}(f(u_{j,c})) < 0.000001 \)

BREAK

In this example, the stopping criteria of the DE algorithm were as follows: if RMSE or MANE values repeated more than n-times (Convergence check value = 40) or if the difference between the current MANE or RMSE value and the average FITNESS value was less than 0.000001 (DE Precision value), then break (stop) DE algorithm.

**IV. RESULTS AND DISCUSSION**

Let us consider an area with N sectors and M zones. For a specific base year, productions and prices are provided as observable data. The set of observed productions and prices data were denoted by \( X^{\text{act}} \in \mathbb{R}^{N \times M} \) and \( P^{\text{act}} \in \mathbb{R}^{N \times M} \) respectively. The suggested technique of this study was tested using data from example C of the TRANUS tutorial.

The region defined in this example was divided into three geographical zones (j = 1, 2, 3), and five economic sectors (n, m = 1, 2, 3, 4, 5). The economic sectors include basic employment, service employment, low-income household, high-income household, and land. The economic sectors can also be classified as transportable and non-transportable sectors. Sectors that are non-transportable must be consumed where they are produced. They usually connect to real estates, such as homes and net gross floor spaces. Transportable sectors might include all types of employment and inhabitants. Explanations and details can be found in [18], [44].

Shadow prices \( (h^p) \) play a significant role (adjustment factor) in the calibration of the TRANUS land-use and activity model, as they represent attributes of the socio-economic system that are not included in the model. This is the reason that shadow prices were selected, besides price factor \( (\lambda^p) \) and elasticity \( (\delta^m) \), for the further calibration procedure in this study.

Table 6 presents the TRANUS default values of the selected parameters against their optimized values using the DE, GA, and PSO algorithms as the optimization techniques and RMSE and MANE as multi-objective functions. Selected parameters are bounded based on highest and lowest TRANUS default values as follows: \( \delta^m = (0.000001, 0.000100), \lambda^p (0, 1) \), and \( h^p = ((-100, 0) \times P^t)/100 \).

| TABLE 6. Optimized values of proposed parameters using the DE, GA, and PSO algorithms against TRANUS defaults |
|---------------------------------------------------------------|
| Parameter          | TRANUS | DE\_RMSE | DE\_MANE | GA\_RMSE | GA\_MANE | PSO\_RMSE | PSO\_MANE |
|---------------------|---------|----------|----------|----------|----------|-----------|-----------|
| \( h_{1} \)        | 0.0     | -2,197.01| -7,746.90| -5,673.97| -6,463.25| -5,840.70 | -2,669.11 |
| \( h_{2} \)        | -7110.98| -11,026.55| -9,417.64| -15,952.20| -8,989.95| -4,973.87 | -6,414.10 |
| \( h_{3} \)        | -937.08 | -818.09 | -484.49 | -42.22 | -1,144.72 | 0.00 | -895.00 |
| \( h_{4} \)        | -1071.56| -573.63 | -460.12 | -3,338.85 | 0.00 | -1,387.15 | 0.0 |
| \( h_{5} \)        | -2025.36| -18,313.35| -41,815.95| -250,000.00| -75,978.22| 0.0 | -1,438.12 |
| \( h_{6} \)        | -4325.13| -5,083.33| -4,120.93| -7,478.47| -5,843.04| -2,052.41 | -1,357.75 |
| \( h_{7} \)        | -1492.78| -1,273.63| -1,309.45| -288.67| -1,786.39| -995.85 | -1,719.37 |
| \( h_{8} \)        | -2194.84| -2,679.06| -1,916.18| -3,733.16| -1,205.80| -2,337.27 | -2,268.13 |
| \( h_{9} \)        | -27820.67| -12,088.21| -32,170.34| -120,000.00| -51,227.95| -26,779.29 | -52,869.53 |
| \( \delta_{11} \)  | 0.0     | 0.0      | 0.0      | 0.0      | 0.0      | 0.0       | 0.0       |
| \( \delta_{12} \)  | 0.0     | 0.0000000054 | 0.0000000054 | 0.0000000054 | 0.0000000054 | 0.0000000054 | 0.0000000054 |
| \( \delta_{13} \)  | 0.0000000054 | 0.0000000054 | 0.0000000054 | 0.0000000054 | 0.0000000054 | 0.0000000054 | 0.0000000054 |
| \( \delta_{14} \)  | 0.0     | 0.0     | 0.0      | 0.0      | 0.0      | 0.0       | 0.0       |
| \( \delta_{15} \)  | 0.0     | 0.0000000054 | 0.0000000054 | 0.0000000054 | 0.0000000054 | 0.0000000054 | 0.0000000054 |
| \( \delta_{16} \)  | 0.0     | 0.0     | 0.0      | 0.0      | 0.0      | 0.0       | 0.0       |
| \( \delta_{17} \)  | 0.0     | 0.0     | 0.0      | 0.0      | 0.0      | 0.0       | 0.0       |
| \( \delta_{18} \)  | 0.0     | 0.0     | 0.0      | 0.0      | 0.0      | 0.0       | 0.0       |
| \( \delta_{19} \)  | 0.0     | 0.0     | 0.0      | 0.0      | 0.0      | 0.0       | 0.0       |
| \( \delta_{20} \)  | 0.0     | 0.0     | 0.0      | 0.0      | 0.0      | 0.0       | 0.0       |

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The calibrated values of the parameters presented in Table 6 show that using the DE algorithm cause none of the parameters’ values stuck to the upper and lower bounds, while GA and PSO detect lower or upper bounds of the parameters as the optimum results, such as $\text{GA}_{\text{MANE}}$ ($\delta_1^* = 0.00001$, $\delta_2^* = 0.000001$, $\delta_3^* = 0.00001$) and $\text{PSO}_{\text{MANE}}$ ($\delta_1^* = 0.000001$, $\delta_2^* = 0.000001$), so they were not able to improve MANE and RMSE values further.

The consistency of the calibration algorithm provided here is demonstrated. Because the DE estimator employing both MANE and RMSE is asymptotically efficient, the estimate is become closer to the real solution as the number of iterations increases, as seen in Fig. 5 and Fig. 6. Furthermore, it is apparent that the optimal cost values were continually reduced by the DE technique. In addition, DE was able to discover better solutions almost in every iteration. As a result, we can state that the suggested calibration technique is capable of reliably estimating the land-use characteristics.

The calibration results of multi-objective optimization (prices and productions) for DE, GA, and PSO optimization techniques started with a similar RMSE value, but PSO stopped its improvement before 100 iterations, while both GA and DE continuously improved RMSE values and ended almost near 1000 iterations.

In addition, the consistency of the calibration algorithm provided here is demonstrated. Because the DE estimator employing both MANE and RMSE is asymptotically efficient, the estimate is become closer to the real solution as the number of iterations increases, as seen in Fig. 5 and Fig. 6. Furthermore, it is apparent that the optimal cost values were continually reduced by the DE technique. In addition, DE was able to discover better solutions almost in every iteration. As a result, we can state that the suggested calibration technique is capable of reliably estimating the land-use characteristics.

Fig. 6 shows that the best RMSE value was obtained by the DE algorithm with a value of 168. However, both GA and PSO were unable to conclude the RMSE values less than 280 and 458, respectively. Here again, all three optimization techniques started with a similar RMSE value, but PSO stopped its improvement before 100 iterations, while both GA and DE continuously improved RMSE values and ended almost near 1000 iterations.

| $\delta_1^*$ | 0.000006 | 0.00000679 | 0.00000754 | 0.00000984 | 0.00000632 | 0.00000333 | 0.00000879 |
| $\delta_2^*$ | 0.00000723 | 0.00000757 | 0.00000621 | 0.00000100 | 0.00000100 | 0.00000100 | 0.00000100 |
| $\delta_3^*$ | 0.00000175 | 0.00000627 | 0.0000288 | 0.00000848 | 0.00000100 | 0.00000100 | 0.00000100 |
| $\lambda_1^*$ | 0.0000306 | 0.0000591 | 0.00000100 | 0.00000100 | 0.00000100 | 0.00000100 | 0.00000100 |
| $\lambda_2^*$ | 0.0000341 | 0.0000618 | 0.0000888 | 0.00007800 | 0.0000846 | 0.0000846 | 0.0000846 |

**TABLE 6.** Observed prices and productions vs, models values using the DE algorithm.

**FIGURE 5.** MANE values of DE, GA, and PSO optimizations.

**FIGURE 6.** RMSE values of DE, GA, and PSO optimizations.
The outstanding performance of the DE algorithm using MANE as the objective function is proved by the results presented in Table 7. The DE calibration technique using MANE objective function enables us to reach the observed production values without any error, and observed price values with a slight difference, whereas the results variation ratios came to between 0.98 and 1.02. However, the DE calibration technique using RMSE objective function can model the observed price and production values with a higher discrepancy, with results variation ratios between 0.94 and 1.05. Only the parameter ($X_3$) was not modeled properly as its Mod./Obs. the ratio is 1.23.

**TABLE 8. Observed prices and productions vs, models values using the GA algorithm.**

| Parameter | TRANUS results | MANE-based results | Mod./Obs. Ratio | RMSE-based results | Mod./Obs. Ratio |
|-----------|----------------|--------------------|----------------|-------------------|----------------|
| $X_1$    | 5000.0         | 5000.0             | 1.00           | 5000.0            | 1.00           |
| $X_2$    | 3500.0         | 3497.7             | 1.00           | 3344.0            | 0.96           |
| $X_3$    | 4000.0         | 3972.5             | 0.99           | 3925.0            | 0.98           |
| $X_4$    | 1500.0         | 1501.1             | 1.00           | 1232.9            | 0.82           |
| $X_5$    | 66.0           | 66.0               | 1.00           | 126.3             | 1.91           |
| $X_6$    | 800.0          | 800.0              | 1.00           | 800.0             | 1.00           |
| $X_7$    | 700.0          | 700.7              | 1.00           | 948.9             | 1.38           |
| $X_8$    | 13000.0        | 13026.4            | 1.00           | 12887.1           | 0.99           |
| $X_9$    | 3000.0         | 2998.8             | 1.00           | 2908.9            | 0.97           |
| $X_{10}$ | 110.0          | 110.0              | 1.00           | 154.5             | 1.40           |
| $X_{11}$ | 1100.0         | 1100.0             | 1.00           | 1100.0            | 1.00           |
| $X_{12}$ | 900.0          | 901.5              | 1.00           | 807.0             | 0.90           |
| $X_{13}$ | 5000.0         | 5000.0             | 1.00           | 5193.6            | 1.04           |

Similarly, as seen in Table 8, the GA calibration technique using MANE objective function exactly modeled the observed production values, while price values had a slight difference with a variation ratio between 0.98 and 1.04. However, the GA calibration technique using the RMSE objective function had a major discrepancy, where the variations of the results were between 0.82 and 1.91. This shows the deficiency of the GA calibration technique using RMSE objective functions.

**TABLE 9. Observed prices and productions vs, models values using the PSO algorithm.**

| Parameter | TRANUS RESULTS | MANE-based results | Mod./Obs. Ratio | RMSE-based results | Mod./Obs. Ratio |
|-----------|----------------|--------------------|----------------|-------------------|----------------|
| $X_1$    | 5000.0         | 5000.0             | 1.00           | 5000.0            | 1.00           |
| $X_2$    | 3500.0         | 3497.7             | 1.00           | 3344.0            | 0.96           |
| $X_3$    | 4000.0         | 3972.5             | 0.99           | 3925.0            | 0.98           |
| $X_4$    | 1500.0         | 1501.1             | 1.00           | 1232.9            | 0.82           |
| $X_5$    | 66.0           | 66.0               | 1.00           | 126.3             | 1.91           |
| $X_6$    | 800.0          | 800.0              | 1.00           | 800.0             | 1.00           |
| $X_7$    | 700.0          | 700.7              | 1.00           | 948.9             | 1.38           |
| $X_8$    | 13000.0        | 13026.4            | 1.00           | 12887.1           | 0.99           |
| $X_9$    | 3000.0         | 2998.8             | 1.00           | 2908.9            | 0.97           |
| $X_{10}$ | 110.0          | 110.0              | 1.00           | 154.5             | 1.40           |
| $X_{11}$ | 1100.0         | 1100.0             | 1.00           | 1100.0            | 1.00           |
| $X_{12}$ | 900.0          | 901.5              | 1.00           | 807.0             | 0.90           |
| $X_{13}$ | 5000.0         | 5000.0             | 1.00           | 5193.6            | 1.04           |
| $X_{14}$ | 15120.0        | 15127.5            | 1.00           | 1505.9            | 1.01           |
| $X_{15}$ | 11703.0        | 11767.0            | 1.01           | 12778.7           | 1.09           |
| $X_{16}$ | 2644.0         | 2584.5             | 0.98           | 2895.3            | 1.10           |
| $X_{17}$ | 3693.0         | 3748.5             | 1.02           | 3948.5            | 1.07           |
| $X_{18}$ | 180000.0       | 179925.3           | 1.03           | 181233.8          | 1.01           |

Considering results presented in Table 9, like both DE and GA results, the PSO calibration technique using MANE
objective function outperformed the PSO calibration technique using RMSE objective function in terms of modeling the observed data.

The technique of creating a new population of solutions by perturbing solutions from the prior population is one of the key distinctions between the three algorithms described above. Within the GA algorithm, the parents are chosen based on probabilities that favor an individual who is physically fit, and the crossover operation creates offspring with pieces from both parents, and the solutions are more likely to be similar to the parents. Finally, the mutation process, which injects some discrepancy into the solutions from time to time, is how GA achieves its diversity.

In the PSO algorithm, as the new swarm of particles is produced via the updates of the positions and velocity of each old individual, therefore, it can be said with confidence that they are much different from the old ones. The PSO algorithm converged so quickly, as seen by the findings, due to the one-way influence of the best particle in the swarm, over all other solutions in the population. This process limited the solution candidates and prevented further improvements.

The DE algorithm improved the process of finding new answers by ensuring that the best solution in the population did not influence the other solutions in the population. In addition, the mutated vector was always a solution that did not come from the original population; therefore, the crossover operation in DE always took place between a population solution and a newly generated one. The further improvement of the DE algorithm was led by this process, unlike both PSO and GA algorithms, as the presented findings by this study.

The suggested calibration technique was carried out by a laptop with the following specifications: Lenovo ThinkPad T440s, CPU: Intel(R) Core TM i7-4600U @ 2.10GHz with 2 Core(s) and 4 Logical Processor(s), RAM: 8.00 GB, and a 64-bit Operating System Win10. The DE, GA, and PSO calibration techniques using MANE carried out the calibration process in 64.1, 45.4, and 40.2 seconds, respectively, while using RMSE it needed 102.7, 79.5, and 51.2 seconds.

V. CONCLUSION AND FUTURE STUDIES

According to the literature reviewed, most of the existing LUTI calibration methods are semi-automated, using single-objective functions, local estimation techniques and they suffer the lack of a global estimation process. There is no standard approach to calibrating LUTI models and neither is there a consensus on which objective function to use. However, their complexity making the calibration of these tools a very expensive, time-consuming, and challenging process. To address these existing limitations, a novel LUTI model calibration technique benefiting from the capability of the differential evolution algorithm is presented in this study. A further step toward all the desires of previous studies in the field is performed by this study, which pivot toward the development of a global and automatic calibration approach for LUTI models.

First, the most important parameters (elasticity, price factor, and shadow prices) of the land-use model were obtained through sensitivity analysis. Then, a DE algorithm was used to calibrate these parameters simultaneously to reach a global minimum using MANE and RMSE as multi-objective functions of both productions (\(X^f_j\)) and prices (\(P^j\)). The sensitivity analysis and the suggested calibration technique were then tested on data from example C of the TRANUS model, and two optimization techniques (GA and PSO) were used to test the performance of the approach, with the usage of the same objective function method (MANE and RMSE). Below is the summary of research findings, limitations, and some recommendations for further studies:

- DE-based optimization allows us to involve multi parameters in the LUTI model calibration procedure.
- In terms of modeling of the observed data (modeled/observed ratio), the suggested DE calibration technique outperformed both PSO and GA-based calibration techniques, using MANE and RMSE multi-objective functions.
- MANE observed values are modeled with no (or low) discrepancy, the successfullness of MANE compared to RMSE multi-objective functions is proved here.
- Continuously improvement of the results using the DE calibration technique was demonstrated by the values of the calibrated parameters, while the use of both GA and PSO meant the results stuck to the upper or lower bound of the defined parameters’ ranges, so further improvement was limited.
- In terms of computational time, calibration techniques using MANE multi-objective function were faster than those using RMSE multi-objective function. In addition, PSO based calibration technique had the best convergence time compared to GA and DE-based calibration techniques using both MANE and RMSE multi-objective functions.
- In sum, to calibrate land-use model parameters, the suggested DE calibration technique employing MANE as a multi-objective function outperformed the usage of RMSE as a multi-objective function, in terms of performance (modeled/observed ratio) and convergence time.
- The suggested technique was tested only on a model with three zones and five sectors. Testing of the suggested technique on a large real-world example is still to be done.
- As an extended version of this study, the authors are working on implementing the suggested calibration technique of one of the well-known macroscopic transport modeling software, PTV VISUM.

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Conflicts of Interest:

The authors declare no conflict of interest.

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