RESEARCH ARTICLE

Agent-Based Simulations Using Genetic Algorithm Calibration: A Children's Services Application

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ABSTRACT With increased pressures and tightening budgets within English Children's Services in the UK, seeking more effective operational and financial management is becoming a more significant topic of discussion. In other sectors, complex data analysis methods provide the aforementioned management improvements through better understanding of current situations leading to better decision making. Currently, investment remains at a slow pace in English Local Authorities due to budget restrictions. In this paper, a potential opportunity is explored with existing publicly available data related to this area. With the help of industry experts, an Agent-Based Model is created to emulate basic Children's Services operations and optimised to fit existing data using NSGA-III. With relatively close matches being achieved with sample authorities, this approach demonstrates promise in advancing analytics capabilities for Children's Services and practical solutions are discussed. With this presented work, it is shown that further expansion and exploration into real-world applications is warranted.

INDEX TERMS Agent-based model, calibration, children's services, data analysis, genetic algorithm, social care.

I. INTRODUCTION

The work of Local Authority Children's Services has been under increasing pressure from both funding cuts and demand during the COVID-19 pandemic. These services have also reported the need for significant changes in policy in recent years prior to the pandemic [1].

One area which is seeing increased interest in recent years, is the improvement of Children's Services Data Analysis capabilities. There have been studies that have proposed the use of machine learning for some decision automation within the Social Care Workforce; this has been met with intense scepticism and reluctance due to concerns around data sensitivity, ethics, and accuracy. [2]

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The state of Local Authority Children's Services data infrastructure and analytics capabilities can be seen as suffering from several key issues, as described in NESTA's Missing Numbers in Children's Services report [3]. Of the issues mentioned in the report, they could be summarised into two groups: infrastructure, and systemic. The first group highlights the fragmented nature of children's services, department of education, social care, and government. With such a fragmented nature, there is multiple data silos within each institution with varying definitions and standards. This leads to inconsistencies with data quality, duplication, and difficulties linking data features or sources together.

Agent Based Modelling [4] has seen use in the wider social sciences, and presents an opportunity to investigate the potential to address these issues and create the analytics capabilities that are desired with the Children's Services.

In summary, the current literature and background to Children's Services highlight a set of issues present in the development of analytics capabilities. Further to this, the issues identified include: the fragmented nature of services, varying data standards and subsequent data quality problems, and a lack of trust in the Children's Services workforce.

Thus, presented in this paper, will be a model and calibration method that may serve as the basis for tools that can fulfil some of the aforementioned needs. The model and calibration method for individual Local Authorities (LAs) that can result in additional value extraction from public data that enhances existing analytics capabilities within LAs.

II. RATIONALE AND EXISTING LITERATURE

The existing literature in Children's Social Care and Social Care in general commonly proposes changes to policy as a source of providing the desirable change in the outcomes of those in Care [1], [5], [6], [7], [8]. Being able to assess these suggestions alongside existing policy could provide LAs with better foresight and more informed decision making. Furthermore, as mentioned previously, currently existing data sources for LA Social Care data is sparse, meaning that LAs would struggle to examine how policy differences between authorities could affect their own outcomes and targets. The ability to compare and understand data and policy between authorities is seen as an important activity by decision makers in LAs, as demonstrated by the Local authority interactive tool (LAIT) provided by the Department of Education [9]. These comparisons help in knowing how well their services are functioning and if there are changes that could be made to improve them. Operational relations between authorities may also benefit from these capabilities, as understanding the effects of taking on demand from adjacent authorities can be seen with a degree of predictability.

It is therefore tempting to explore the possibility of using new and popular techniques within machine learning (ML), such as Neural Networks [10], to automate work and provide predictive capabilities to Local Authorities. As this has shown promise in existing literature [11].

This however, is not likely the best approach. What Works for Children's Social Care [2] implemented a risk assessment tool that looked at case data for a given child being seen by a social worker, and then classified the 'risk' the child was currently in. In this study it was noted that two different issues will likely cause particular difficulty in utilising ML in Children's Social Care.

Firstly, it was shown that the model created was only satisfactory in its ability to correctly assess the risk to children. This is likely due to the complexity of Social Care cases, data availability/quality, and if such data is sufficient for determining the risk to a child.

Secondly, there is high resistance to any kind of automation and a general distrust of such decision-making systems (Automation Bias [12]). A subsequent survey was carried out by What Works for Children's Social Care, to assess social worker's views on the tool and future ML powered tools for

social care work. The survey found that only around 10% of social workers would trust/consider using such a system for their own work.

This therefore, points to a challenge when developing ML based decision support systems for this domain. Decision Support Systems have been observed in related areas to Children's services when examining existing literature [13], [14], [15]. Typically, ML decision systems currently in use look more towards automating a form of low-level human cognitive ability for an improvement in speed, such as Computer Vision [16] and Natural Language Processing [17]. However, in this domain, the task is more reliant on intuitive human social skills and emotional understanding to spot and identify a given child's needs and deliver the appropriate care for them [18], [19], [20], [21].

Thus, a potentially different approach may need to be considered for domains such as this. When considering the application of ML to tasks/problems in this domain, trust and transparency should be highlighted in the development process; two key ideas that have seen a rise in popularity in recent years within ML research [22], [23], [24]. This with a focus on augmenting, rather than automating, local authorities and social workers abilities may lead to better acceptance and results for future tools.

An alternative to the current popular ML approaches could potentially be Simulation techniques applicable to Social Systems [25]. The most prominent choice in the literature would be Agent-Based Models (ABMs) [4]. ABMs have been used extensively previously in modelling systems that represent social systems requiring interaction between entities. The context of the work conducted within LAs is therefore conducive to this type of modelling.

Simulations present several useful advantages that fit with the issues with presented earlier. The first being in establishing a common language or framework to conduct analysis. With a common framework in place, those of differing roles with LAs could contribute to the model design and analysis. Social workers, decision makers, and support staff all have vast experience and knowledge of how children's service practice is delivered; with the use of simulations, this information could be mobilised into more effective models of how LAs operate [26].

Further to this, the use of a common simulation model for analysis, creates a mode of communication between decision makers and data analysts, and reducing turnaround for queries and analysis of policy or decisions.

Alongside these advantages, simulations could provide useful analysis for LAs in finding leverage points in existing services and are able to capture the complex set of features present in LA operations, such as population, social determinants, workforce, and budget [3], [26].

ABMs specifically, provide certain advantages that would appear to fit the domain of children's services better than other methods. Firstly, ABMs focus on individual level interactions and 'micro' level parameters which could be related to practice and service delivery in LAs by social workers [27].

Furthermore, implementing such ABMs would be conceptually and practically straightforward for existing LA data analysts with the availability of libraries such as Mesa [28], [29] for Python. The expansion of the tools utilised by data analysts in LAs would also further the recommendations made in the previously mentioned Missing Data in Children's Services report [3] and others [30], namely the increase in data and data science literacy.

As a result, the simulation technique chosen for this report will be Agent-Based modelling. This however, may not fully meet the needs presented earlier, as there would potentially be a multitude of parameters that could govern such a simulation of Children's Services.

Therefore, it is desired that the approach used should also include a method for selection of appropriate parameter values. This is due to each Local Authority being subject to variances in operational policy, workforce structure and budgets (which have been observed for some time) [3], [31], [32] that would need to be considered for using a given simulation. Additionally, with the data quality issues mentioned previously, some of these parameter values may not be immediately available from existing public data sources.

An optimisation technique will need to be selected to carry out this parameter selection, based on what existing data there is from public sources.

When exploring the literature regarding this, a key candidate for an optimisation technique, would be a Genetic Algorithm. This approach can be seen to be used in optimising other ABM based simulations in other domains [33], [34], [35], [36], [37]

Furthermore, using such an optimisation method may be advantageous route that can help in creating additional value from the sparse public data already available, as the values approximated for each LA can serve as new data points that can be further analysed for insight. Machine Learning regression techniques were also observed when optimising an ABM [38], [39], this however represents a small and emerging section of the literature. Therefore, a genetic algorithm approach was chosen due to the established literature.

A. RELATED WORK: GA OPTIMISED ABMs

When exploring existing literature around the aforementioned concept of ABM optimisation, the most prominent technique found was the use of a Genetic Algorithm (GA) to conduct the optimisation or calibration.

Previous use of GA calibrated ABMs by researchers has been seen in a limited, but successful set of literature, which explore various contexts and report notable results and suggestions.

Heppenstall *et al.* [40], discuss the use of this method for simulating the retail petrol market. It is seen that the presented ABM and GA calibration can result in a close agreement in the parameters chosen by the GA and the real parameter values. This, in turn, leads to the suggestion that there is likely only a limited number of possible solutions when using an ABM with constraints.

This conclusion hints to a likely observation that, due to the numerous regulations and constraints used for Children's Social Work, this approach should yield only a limited set of solutions for a given Local Authority, which will be helpful as the correct parameter value set could be determined by further analysis more easily.

It is noted that there is no observed use before of this method being used in this context. This inherently presents an opportunity to explore the application of this method and explore the benefits and potential challenges that can aid in future research.

The points demonstrated by Heppenstall *et al.*, can also be seen in others attempting the same approach [33], [34], [35]. These limitations will be considered in this report, in particular when designing how this approach is implemented.

B. RELATED WORK: ABMs AND SYSTEM DYNAMICS RELATED TO SOCIAL CARE

More in line with the domain in this report, the work of Mouratidis *et al.* [37] discusses the use of an ABM for the health and social care sector. Namely modelling the delivery of care to older people by various types of care workers and the administrative processes related to this work.

The conclusion of the report suggests that there is a lack of dedicated software tools for conducting the appropriate level of analysis needed to make the ABM the most beneficial.

Since the publication of the report, there has been major developments in the tooling available to produce and analyse ABMs [28]. Therefore, it is appropriate to re-investigate the use of ABMs in the Social Care sector, as literature in this area has been sparse.

More recently, there has been work conducted that looks at more targeted intervention and policy evaluation using Simulations (in this case System Dynamics [41] rather than ABMs). The work presented in Occhipinti *et al.* [42] report covers the use of a System Dynamics Model for evaluating the potential effect of interventions and changes to policy for preventing teenage suicide via children's services.

The results presented and the conclusions made point towards the validity of simulations in performing this kind of analysis and should be used to help in investigating viable new solutions for tackling these issues.

III. MODEL DESIGN AND CALIBRATION METHOD

In order to examine and evaluate the potential for the proposed approach, an experimental methodology was used where a sample of LAs were selected and used; as per existing literature approaches [25], [33], [34], [35], [37], [40]. Each LA had an ABM calibrated using a multi objective fitness function. The calibration used specified public data to optimise parameters of the model; additional unseen data was also used to compare some parameters of the model to aid in validating the results and conclusions.

As noted in previous work, computation time was likely to become an issue [40], thus the selection criteria for the sample LAs was based on the number of Social Workers present in

TABLE 1. Regions of england and the selected LA from each.

Region	Local Authority
North West	Warrington
North East	Darlington
Yorkshire and the Humber	York
East Midlands	Rutland
West Midlands	Herefordshire
East of England	Luton
Inner London	Hammersmith & Fulham
Outer London	Merton
South East	Bracknell Forest
South West	Bath & North East Somerset

FIGURE 1. High-level view of simple local authority ABM.

TABLE 2. Configurable parameters of the ABM.

Parameter	Symbol
Average Referral Length	R_{Length}
Average Assessment Length	A_{Length}
Average CIN Length	CIN_{Length}
Average CPP Length	CPP_{Length}
Average CIC Length	CIC_{Length}
Referral No Further Action Rate	R_{Rate}
Assessment No Need Rate	A_{Rate}
CIN Conversion Rate	CIN_{Rate}
CPP Conversion Rate	CPP_{Rate}
CIC Conversion Rate	CIC_{Rate}
Pre-allocation Referral Limit	R_{Limit}
Pre-allocation Assessment Limit	A_{Limit}
Pre-allocation CIN Limit	CIN_{Limit}
Pre-allocation CPP Limit	CPP_{Limit}
Pre-allocation CIC Limit	CIC_{Limit}
Pre-allocation Referral Range	R_{Range}
Pre-allocation Assessment Range	A_{Range}
Pre-allocation CIN Range	CIN_{Range}
Pre-allocation CPP Range	CPP_{Range}
Pre-allocation CIC Range	CIC_{Range}

TABLE 3. Input parameters of the ABM.

Parameter	Symbol
Daily Referral Demand	R
Social Workers	SW
Average Worker Caseload	$AFWC$

of existing work for new Social Worker hires within LAs. These processes were based on the statutory guidance provided by the Department of Education regarding Children's Services [43].

Figure 1 summarises the aforementioned design and expected behaviour from each agent type.

The two-agent approach was chosen to help produce a high-level model of the LA behaviours. This model could be greatly expanded to cover several social worker and administration role variations as seen in Mouratidis *et al.* [37] work.

The parameters selected for the final model design were done so with the intention of having a much of the model configurable as possible. This was desired as it was believed that this may give the model the most likely chance to approximate the varied LAs outputs as possible.

The final parameters can be grouped into differing application areas: Environmental, Case Lengths, Conversion Rates, Starting Case Limits, and Starting Case Age. The resulting number of parameters used was 20, as per table 2.

To help with conciseness, several acronyms have been used to when describing aspect of the ABM going forward, these include:

- FTE - Full Time Equivalent, unit of work used by the Children's Social Work Workforce Census [44].
- AFWC - Average FTE Worker Caseload, measure of workload used by Department of Education [45].
- CIN - Children in Need.
- CPP - Child Protection Plan.
- CIC - Children in Care.
- MSE - Mean Squared Error [46].

the LAs. The LA with the fewest Social Workers was selected from each region of England, which resulted in 10 samples.

Based on this criterion, the following LAs were used as samples, as seen in table 1.

Following on from this, the model used for the experiment was kept simple in order to help identify shortcomings with existing assumptions regarding LA workforce management before proceeding with future work. It consisted of two agents of different quantity: A single Children's Social Care Services (CSCS) Agent, and multiple Social Worker Agents. These represent the highest-level distinction between the administrative work conducted by the LAs when delegating work, and the front line care work handling individual cases.

Thus, the CSCS Agent's desired processes could be summarised as: the delegation of new work (Referrals) to Social Workers, and the handling of LA statistics. The Social Worker Agent's processes can also be summarised as: the handling of new and existing cases assigned to themselves, within the LA. One further process for the Social Worker Agents was added, that being the pre-allocation of existing work based on current caseload. This was required for two reasons, firstly for initialisation purposes at the beginning of each simulation, and secondly for the addition of new social workers during the simulation. This would then emulate the redistribution

A. REFERRAL ALLOCATION SIMULATION

Referral allocation is simulated by using the creation of new referral cases to random existing social worker agents, up to the *Ref* value for the given simulation step.

B. WORKER AGENT MANAGEMENT

Worker agents are managed by the CSCS agent using algorithm 1. The difference in social workers from the previous simulation step to the current step is used to determine if the CSCS agent creates or removes social worker agents from the ABM. The allocation of an existing worker cases to either a new worker agent or from an to be removed worker is done in a random manner. This is to ensure a uniform distribution of worker caseload within the simulation. The calculation used to determine the change in social workers can be seen in equation 1:

$$diff_{SW} = SW_{Current} - SW_{Previous} \qquad (1)$$

Algorithm 1 Social Worker Agent Management Algorithm

Require: $diff_{SW}$ ▷ Calculated using Equation 1
  if $diff_{SW} \geq 1$ **then**
      $Agent \leftarrow SocialWorker()$
      ▷ Creates a new instance of the Social Worker Agent.
      $Agent.cases \leftarrow SelectRandomCases()$
        ▷ Selects random cases from existing Agents.
  end if
  if $diff_{SW} \leq -1$ **then**
      $Agent \leftarrow SelectRandomSocialWorker()$
      for $case \in Agent.cases$ **do**
         $Worker \leftarrow SelectRandomSocialWorker()$
         $Worker.cases \leftarrow Worker.cases \cup case$
           ▷ Re-allocates selected Agent's work.
      end for
  end if
  if $diff_{SW} = 0$ **then**
      pass   ▷ No change in Social Workers.
  end if

C. PRE-ALLOCATION PROCESS OF EXISTING WORK

In order to simulate the existing caseloads before the ABM is ran, the age of each case is determined using case type specific range parameters in the form of algorithm 2. These are limited using the respective length parameter to ensure consistent case lengths of the pre-allocated and subsequent cases. Finally, the amount of each case type is determined using the respective limit parameters.

D. CASE MANAGEMENT SIMULATION

To simulate the workflow of Social Workers within the ABM, each case is processed, and actions are decided using the length and conversion rate parameters, as per algorithm 3. If the age of a case exceeds the respective length parameter, then the case may advance to the next case type, subject to the

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Algorithm 2 Age of Pre-Allocated Referrals Algorithm

Require: $R_{Length} \geq 0$ ▷ Average referral length cannot be less that 0.
Require: $R_{Range} \geq 0$ ▷
  $Age \leftarrow Rand(R_{Length} - R_{Range}, R_{Length})$ ▷ Rand(x,y) is a uniform random generator between x and y

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Algorithm 3 Referrals Case Management Algorithm

Require: $R_{Rate} \geq 0$ ▷ Conversion rate of Referrals to Assessments
Require: *Agent*
  for $case \in Agent.cases$ **do**
      if $case.type = Referral$ **then**
         if $case.age \geq R_{Length}$ **then**
             ▷ Case age exceeds set average length.
            $r \leftarrow Rand(0, 1)$
            if $r \geq R_{Rate}$ **then**
            ▷ Case advances from Referral to Assessment.
               $case.type \leftarrow Assessment$
               $case.age \leftarrow 0$
         end if
      end if
      $case.age \leftarrow case.age + 1$
            ▷ Increase the age of the case by 1 day.
  end if
  end for

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probability set by the respective rate parameter. Once a case has been processed, the age of the case is increased by 1 day.

E. MULTI-OBJECTIVE CALIBRATION

The calibration process evaluates several objective functions against target data by simulating the model for one year (365 steps) to allow for the optimisation of the ABM input parameters. The objective functions were chosen to measure the error of the ABM in both quantitative and qualitative aspects. During calibration, actual interpolated data is given to the model for the three inputs mentioned previously: Number of Social Workers, referral demand, and starting social worker caseload. The data collected over the simulation period is then evaluated using the objective functions, which are based on MSE and Population Variance as per equations 2 and 3.

$$MSE = \sum_{i=1}^{n}(x_i - y_i)^2 \qquad (2)$$

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n} \qquad (3)$$

The objective functions used to evaluate the ABM performance can be seen in the following:

- Error of Average FTE worker caseload at end of simulation (MSE).

- Error of Average FTE worker caseload over year (MSE).
- Error of CIN Cases (MSE).
- Error of CPP Cases (MSE).
- Population Variance of the number of active Referrals (less than 25 results in no penalty).
- Population Variance of the number of active Assessments (less than 50 results in no penalty).
- Population Variance of the number of active CIN plans (less than 200 results in no penalty).
- Population Variance of the number of active CPPs (less than 200 results in no penalty).
- Population Variance of the number of active CIC plans (less than 200 results in no penalty).
- Sum of the number of active daily CIC plans (more than 1000 results in no penalty).

As mentioned previously, these functions cover both quantitative and qualitative aspects of the model's evaluation. For the quantitative, the model should be optimised for the amount of CIN cases, CPP cases, and AFWC that were observed by the selected LA in the real data. For the qualitative, the model should be optimised for having a minimal (or subjectively realistic) amount of variance in the amounts of active referrals, assessments, CIN, CPP, and CIC cases observed in the real data. The intention with this approach is to adequately constrain the potential parameter values that the calibration method could apply to the model successfully, and therefore converge on more optimal configurations.

The functions mentioned previously also include methods for weighting and normalisation, due to different value magnitudes within the input data, to ensure that specific measures had the desired priority in the respective function. In order to achieve this, a simple normalisation function was written that reduced the amount of error produced by the measures, by the proportion of the input's absolute value. In testing, it was found that this approach created the intended priority, with the measures around worker caseload receiving favour. With these functions in place the model and calibration method were complete, the final step before final assessment was to determine the appropriate parameter values for the GA calibration.

In order to select the appropriate parameter values for the GA based calibration method, iterative experimentation was conducted. Two variants of GA have been introduced in this study such as NSGA-II [47] and NSGA-III [48] were compared to ascertain the most appropriate algorithm for this objective function(s). Upon testing, both algorithms converged, with NSGA-III converging faster in the samples. It can also be seen in the literature that NSGA-III may be more suitable for multi-objective problems presented by Ishibuchi *et al.* [49]. Therefore, the algorithm used was NSGA-III.

Based on the work of Hassanat *et al.* [50] a range of candidate values was decided and tested with the model and calibration method using the smallest LA of the samples (Rutland) to minimise computation time. The resulting values for Population Size and Iterations were 80 and

TABLE 4. Input data for the GA calibration process.

Local Authority	*SW*(S)	*SW*(E)	*R*(S)	*R*(E)	*AFWC*
Warrington	125	124	4.72	3.91	22.10
Darlington	81	84	6.18	3.02	12.50
York	105	100	3.39	3.04	15.30
Rutland	19	23	1.05	0.98	16.90
Herefordshire	91	92	3.75	3.24	16.90
Luton	111	103	9.48	6.73	21.30
Ham & Fulham	135	143	5.35	4.23	13.40
Merton	120	127	4.30	6.03	15.10
Bracknell Forest	70	76	4.50	6.14	16.00
Bath & NE Som	97	107	3.17	2.76	17.00

TABLE 5. Target and simulated output data from the GA calibration process.

Local Authority	CPP(M)	CPP(R)	AFWC(M)	AFWC(R)
Warrington	412	440	18.08	17.60
Darlington	192	208	14.42	16.40
York	379	374	17.48	17.70
Rutland	44	43	14.96	14.90
Herefordshire	433	422	17.02	16.50
Luton	464	504	23.92	23.90
Ham & Fulham	262	275	12.84	12.90
Merton	333	372	15.70	17.70
Bracknell Forest	364	340	13.62	13.80
Bath & NE Som	315	315	14.17	14.00

75 respectively. Mutation Rate and Crossover Rate were 0.01 and 0.95. With these values determined the final calibrations runs of the model against each LA were undertaken.

The input data for the calibration process was selected from the 2017 to 2018 period, as to remove any possible irregularities produced by the COVID-19 Pandemic in more recent data. This data was then acquired through the PHE Fingertips API, a summary of which can be seen in table 4 with symbols in table 3, with Starting number of Social Workers (SW(S)), Ending number of Social Workers (SW(E)), Starting number of daily Referrals (Ref(S)), Ending number of daily Referrals (Ref(E)), and Starting Average FTE Worker Caseload (AFWC(S)) [51].

When evaluating the performance of the calibration process, the optimisation criteria mentioned previously will be examined and further comparisons will be made between the model outputs and publicly available data, namely comparing the found parameter values determined by the calibration process. A high-level representation of the calibration process can be seen in figure 2.

IV. RESULTS

Tables 5 through 8 show that the ABM and GA calibration process was able to approximate the sample authorities in the majority of the objective functions described previously. These tables include the model (M) produced values and real (R) data, alongside the values for the variance-based (V) objectives, the interpolated (I) average worker caseload and Mean Squared Error (MSE) based objectives. The non-zero function (Z) for CIC cases is also included.

During the initial testing of the calibration process, some of the samples scored poorly compared to other samples.
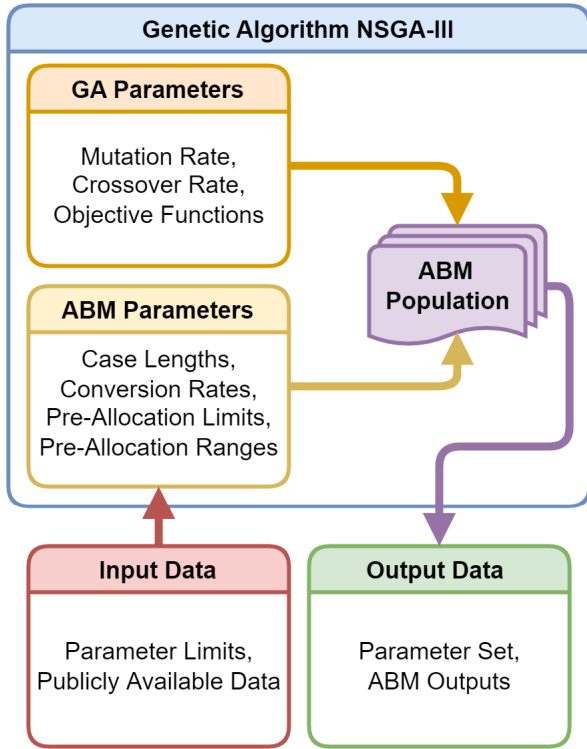
FIGURE 2. Complete overview of the calibration process.

TABLE 6. Error data from the GA calibration process.

Local Authority	AFWC(MSE)	CPP(MSE)
Warrington	0.23	0.78
Darlington	3.93	0.26
York	0.05	0.025
Rutland	0.003	0.01
Herefordshire	0.27	0.12
Luton	0.0005	1.60
Ham & Fulham	0.004	0.17
Merton	4.00	1.52
Bracknell Forest	0.03	0.58
Bath & NE Som	0.03	0.00

TABLE 7. Variance error data from the GA calibration process.

Local Authority	R(V)	AS(V)	CIN(V)	CPP(V)	CIC(V)
Warrington	0.54	6.09	2.94	1.62	0.00
Darlington	0.99	0.00	1.13	2.12	0.00
York	0.00	0.00	0.00	0.00	0.00
Rutland	0.00	0.00	0.00	0.00	0.00
Herefordshire	0.00	0.00	0.68	0.00	0.00
Luton	0.61	0.00	0.00	0.00	0.00
Ham & Fulham	0.00	0.00	0.00	0.00	0.00
Merton	0.00	0.00	2.08	0.00	0.00
Bracknell Forest	0.00	0.00	0.52	0.00	0.00
Bath & NE Som	0.00	0.00	1.18	0.00	0.00

Upon further investigation, it was noted that the CIN Cases MSE function was always significantly higher in the problem samples. The CIN data used for the calibration process was reviewed and concluded that the definition of CIN case in this context of the simulation did not match the definition within

TABLE 8. Remaining error data from the GA calibration process.

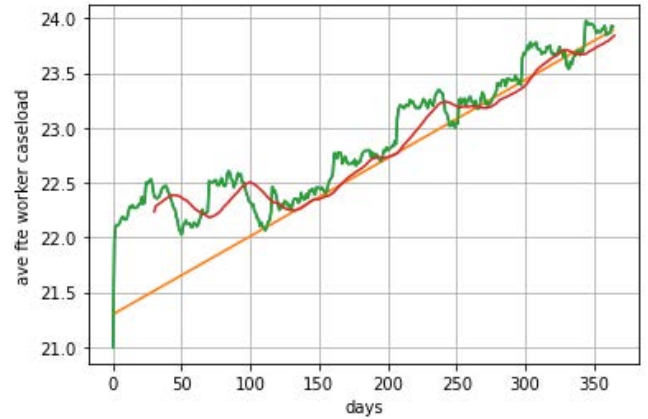| Local Authority	AFWC(I)	CIC(Z)
Warrington	3.73	2.85
Darlington	1.87	0.00
York	0.29	0.00
Rutland	0.18	0.00
Herefordshire	0.13	0.00
Luton	0.16	0.00
Hammersmith & Fulham	0.01	1.36
Merton	1.13	0.00
Bracknell Forest	0.11	0.00
Bath & North East Somerset	0.34	0.00

FIGURE 3. Luton output AFWC from the calibrated ABM. Daily caseload (Green), 30-Day rolling average caseload (Red), and target interpolated caseload from available data (Orange) are depicted.

the Children in Need data, as the definition provided left some ambiguity as to the whether it was tracking an individual case of need as one 'episode' or that each point of interaction with Children's services was an 'episode'. Furthermore, this definition included referrals as part of the 'episode', whereas what was being modelled only referred to the CIN case. Due to this the CIN Cases MSE function was removed from the objective function, and a significant improvement in the scores achieved and the flexibility of the model was seen. This action also eliminated an observed issue where samples with more social workers return higher error scores. This may be reviewed in future work to clarify the definition, however for the purposes of this report, this will be ignored. [52]

Based on the results of the 10 samples, there has been some notable difference in the outputs produced. The most noted difference was that three of the samples: Warrington, Darlington, and Merton failed to converge as well as the other samples. As a result, the majority of the samples produced outputs closely matching the calibration data. This can be seen in figures 4 through 5.

This may be attributable to the simplistic design ABM that does not capture some complexities of social worker practice and case types. One aspect that was not modelled, was the process of re-referrals [53], [54], whereby children with experience in the system are liable to return some time later after some form of early intervention is made. Further to this, dynamics related to de-escalation and escalation [55]
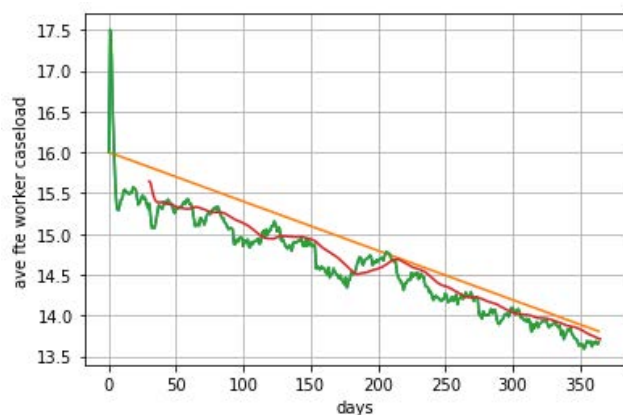
FIGURE 4. Bracknell forest output AFWC from the calibrated ABM. Daily caseload (Green), 30-Day rolling average caseload (Red), and target interpolated caseload from available data (Orange) are depicted.
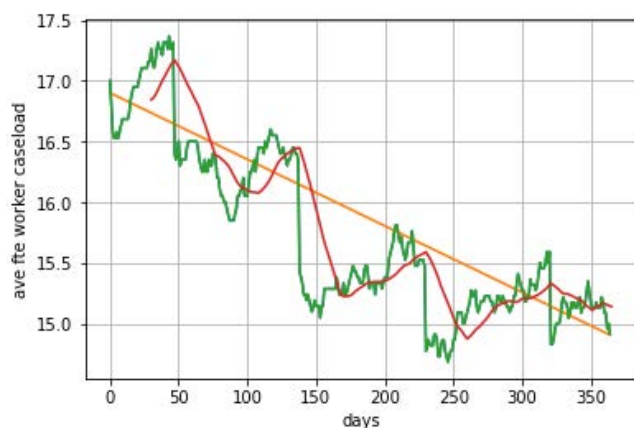

FIGURE 5. Rutland output AFWC from the calibrated ABM. Daily caseload (Green), 30-Day rolling average caseload (Red), and target interpolated caseload from available data (Orange) are depicted.

of cases are also not modelled. These dynamics would lead to the prolonging of certain children interacting with care services, potentially increasing workload overall. This may explain why the GA failed to find as optimal parameter configurations that fit the samples.

With the measures that were selected for the evaluation of the parameter configurations under the optimisation of the GA, they appeared to result in believably representative outputs in worker caseload, active referrals, assessments, children in need, child protection, and children in care cases. For worker caseload, this can be observed in the previously mentioned figures 3 through 5; where the caseload value does not vary significantly beyond the intended target, with exception of the very beginning of the simulation period.

To expand on this, the very beginning of the simulation highlights an implementation limitation of the ABM, namely that the starting caseload parameter value necessitated being an integer. This was due to the workload pre-allocation process within the social worker agents in the ABM. This process required an integer creating an equal amount of existing cases for a given social worker at the start of the simulation period.

This can be seen as a design simplification on the part of the social worker agents, which could be improved upon by using an approach that uses a calculated distribution of caseload values that could then be applied to the social worker agents, this in turn, would eliminate the need for an integer for this parameter value.

When looking at the active case sub-types (referrals, assessments, CIN, CPP, CIC); there can be seen that for the majority of these across the samples, that the output did not include any extreme variance, the believable levels of variance were determined by using the existing data for available case types. Based on, for example, the Children in Care counts from PHE Fingertips [51], where amounts do not vary more than 10-20% for the sample authorities given. The levels of variance in these types of cases did not result in large penalties in combined error score for the selected parameter configurations. This further highlights how the ABM, despite simplistic design, was able to capture and emulate differing levels of these types of cases with reasonable outputs.

An exception to this however would be in CIC cases. During initial testing, the GA selected parameter configurations that neglected this type of case with regards to any extreme variance. This led to some configurations that started with a number of pre-allocated CIC cases and then subsequently did not have any more occur during the simulation period, resulting in no CIC cases being present by the end of the simulation. This was clearly an unrealistic scenario for any LA to experience based on the 10 to 20% variance previously discussed and necessitated the addition of a further measure to ensure that there were always a reasonable number of CIC cases that occur over the simulation period. This measure calculated a penalty error that would be added to the combined error score if there were less than an average of 3 active CIC cases per day over the simulation period. This was implemented by proportionally adding a penalty if the sum of active CIC cases per day was less than 1000 over the period. In later testing, this additional measure aided in reducing the incidence of such variance in CIC cases. However, not all instances of this issue were eliminated. One of the sample LAs, Warrington, still demonstrated this issue, albeit more mildly than in initial testing.

When looking to validate the parameter configurations and outputs produced, some of the parameters used can be found to have analogous features in the publicly available data. Thus, the values chosen for these parameters were compared to public data. Tables 9 and 10 shows the comparison between the GA chosen values for Referral No Further Action rates, Assessment Not in Need rates and for Children in Care case counts with the values available from existing data releases [45], [51].

When looking at these comparisons, it is clear that many are not reasonably accurate. However, the simplistic nature of the model and the limited data given to calibrate with should be considered when examining these values. Furthermore, what this demonstrates, is the need for further work on this approach, with a more sophisticated ABM and more

TABLE 9. Comparisons between the conversion rate data from the GA calibration process.

Local Authority	Ref(M)	Ref(R)	AS(M)	AS(R)
Warrington	0.496	0.090	0.153	0.287
Darlington	0.040	0.069	0.361	0.374
York	0.178	0.064	0.028	N/A
Rutland	0.627	N/A	0.238	0.364
Herefordshire	0.695	0.559	0.208	0.152
Luton	0.629	0.012	0.027	0.474
Ham & Fulham	0.628	0.082	0.020	0.379
Merton	0.231	0.063	0.331	0.371
Bracknell Forest	0.442	0.072	0.525	0.273
Bath & NE Som	0.422	0.025	0.163	0.278

TABLE 10. Comparisons between the output CIC data from the GA calibration process.

Local Authority	CIC(M)	CIC(R)
Warrington	0	400
Darlington	188	215
York	33	195
Rutland	38	30
Herefordshire	55	315
Luton	16	380
Ham & Fulham	2	230
Merton	757	155
Bracknell Forest	40	49
Bath & NE Som	16	170

calibration data. Additionally, due to the large search space for the given parameters, it may be the case that there are multiple configurations that satisfy the given calibration data, meaning that more work is needed to optimise the parameter space search by the GA or other methods.

Overall, the use of the ABM in conjunction with parameter optimisation with a GA was able to get to a reasonable level of accuracy to the publicly available data it was trained against. This is not without limitations, as will be discussed shortly; however, the potential that is demonstrated with this simplistic ABM is such that further expansion and research work is warranted.

V. DISCUSSION

The aforementioned results and limitations identified, the effectiveness of the approach used can be seen. Namely that the simple representation of LA operation and social worker practice, in conjunction with the GA optimisation, produced configurations that reasonably approached the real reported public data.

When looking back at the literature examined for previous use of this approach, one factor that appeared was computation time. The issues relating to computation time, as discussed by Heppenstall *et al.* [40], were demonstrated here by the substantial increase in processing time needed for LAs with more social workers and thus more agents in the simulation. Improvements were made during the development that resulted in a majority decrease (approx. 66%) in computation time. When this optimisation was done, the main sources of additional demand on computation were around iteration through social worker agents and inter-agent
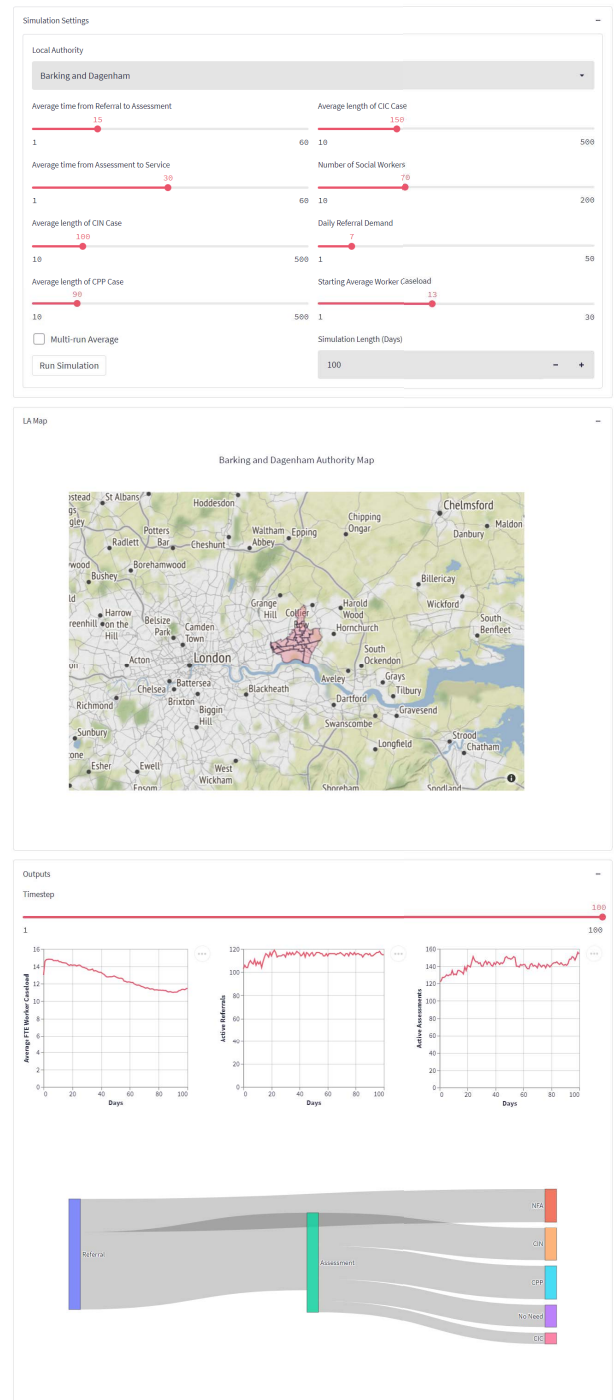

FIGURE 6. Prototype system for utilising the approach demonstrated.

variable updates. One conclusion from this work is that such actions should be avoided/optimised to help increase performance of future implementations of this type of ABM/GA calibration.

This issue could be seen as a key barrier that would need overcoming to allow for effective use of these models

and simulations in practical contexts. Currently however, the existing state of data infrastructure with this domain, Children's Services, is such that this issue may be of limited concern. As mentioned previously, the addition of new data to existing public sources is on an annual basis [51]. This presents an opportunity for this approach to be utilised immediately due to an infrequent need to refresh parameter configurations with the GA.

This however, may only be the case for a limited time, as seen with the further need and demand for improving the analytics capabilities of Children's Services [3], [30]. Thus, there is still a need for the improvement of the computation time required for the parameter optimisation.

The limitations and shortcomings identified should be rectified in any future work and can be done so easily. This is a result of the wide tooling available for building ABMs [28], whereby the Mesa library [29] was utilised for this model. With further refinement and expansion to the design of the model processes, the viable approach shown here is likely to result in a model that will be capable to delivering useful insights to appropriate users.

Following on from this, is where should such a model be utilised for evaluating the effectiveness of Children's Services. One of the first areas that can be seen as a use case for such models and simulations, would be scenario planning and policy evaluation, as seen in previous literature [42]. With having a model that can closely emulate the real public data, given events or conditions could be evaluated by dynamically assigning parameter values based on the step of the simulation. The resulting impact could then be capture via outputs collected from the model and subsequently analysed.

Therefore, this model and approach could be used as part of a decision support system that examines the potential of events on the operational capacity of Children's Services. This could then provide data analysts within LAs the ability to conduct more effective policy evaluation via the use of these simulations, as per public health in existing literature [26]. This has the added benefit of only requiring existing public data sources for the GA to effectively optimise the ABMs parameters, meaning that no additional data processing, cleaning, and storage would be required for LAs to make use of any tool built on this simulation (see Figure 4).

VI. CONCLUSION AND FUTURE WORK

The results presented in this paper show promise regarding the use of this model and calibration method for the intended purpose of extracting additional value from existing Children's Services public data. With some further refinement, the model could approximate a wider variety of LAs real data more effectively.

Several limitations have also been discussed that are of interest for future work. These include improvements that could be made to both the ABM and the GA calibration method. The objective of this report was to evaluate the potential of the approach presented and to consider the next stages of future work that could result. In this regard, the

approach demonstrates that this combination of techniques presents a new opportunity for Children's Services decision makers and analysts, who would likely benefit from the improvements that could be provided if this approach was integrated into existing or new decision support systems for policy evaluation and scenario planning.

Further work with this approach should aim to expand the scope of the ABM used, and include more complex dynamics relating to care practice, as discussed previously. Furthermore, the GA parameter optimisation method used here could be investigated further and compared to other approaches seen recently in the literature such as machine learning surrogate models [56], that may aid in the computation time needed for such parameter space search problems.

Overall, with the increasing demand for more usage of advanced analytics and data utilisation techniques within Children's Services, the approach demonstrated here can act as the basis for more sophisticated simulation implementations that can be used for augmenting decision making within LAs. With this in mind, the limitations presented should serve as the starting points for future investigations.

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