Mathematical and Computer Modeling of Electro-Optic Systems Using a Generic Modeling Approach

M. I. Smith
Waterfall Solutions Ltd.
Surrey GU2 9JX, England, U.K.
moira.smith@waterfallsolutions.co.uk

D. J. Murray-Smith
Centre for Systems and Control
and Department of Electronics and
Electrical Engineering
University of Glasgow,
Glasgow G12 8QQ, Scotland, U.K.
djms@elec.gla.ac.uk

D. Hickman
Waterfall Solutions Ltd.
Surrey GU2 9JX, England, U.K.
duncan.hickman@waterfallsolutions.co.uk

The conventional approach to modeling electro-optic sensor systems is to develop separate models for individual systems or classes of system, depending on the detector technology employed in the sensor and the application. However, this ignores commonality in design and in components of these systems. A generic approach is presented for modeling a variety of sensor systems, operating in the infrared waveband, that also allows systems to be modeled with different levels of detail and at different stages of the product life cycle. The provision of different model types (parametric and image-flow descriptions) within the generic framework can allow valuable insights to be gained.

Keywords: Electro-optic sensor system, infrared, generic model, computer simulation

1. Introduction

In the application of modeling and simulation techniques models are often created on a one-off basis for a specific task. In industry, new designs of engineering systems, similar in many ways to earlier systems, often spawn completely new models [1]. Also, these models are seldom validated or adequately documented. A poorly-documented model of questionable validity is unlikely to be widely used, let alone reused. This paper outlines an approach to the development of generic models for electro-optic systems. The approach encourages reuse of models and offers a rigorous approach to validation and documentation.

2. Electro-Optic Systems

Electro-optic (EO) sensors convert photons into electrical signals. They are used within EO systems for imaging, and different technologies allow operation of EO systems over the ultraviolet, visible, and infrared wavebands. Applications include infrared search and track (IRST) systems, missile warning systems (MWS) and thermal imager (TI) systems.

EO sensor systems involve a number of elements,

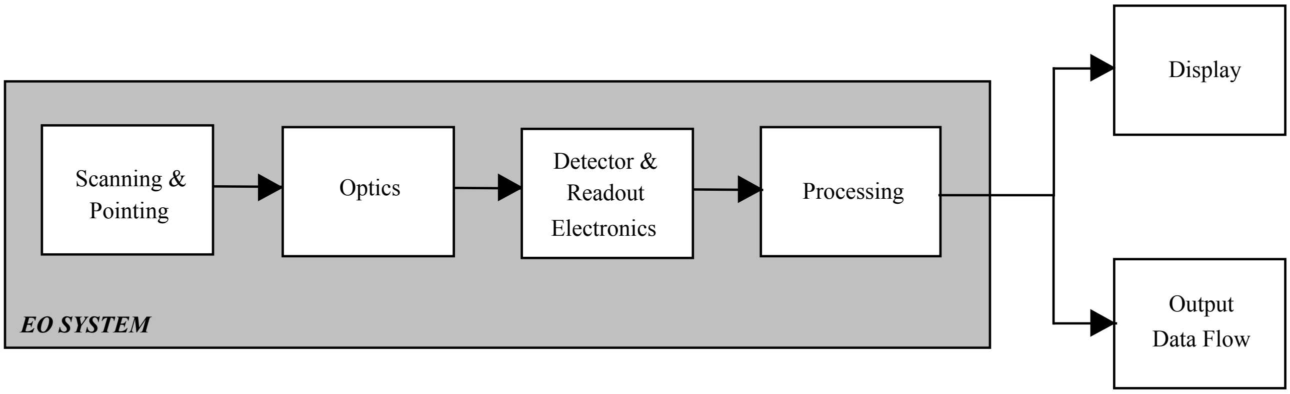


Figure 1. Basic electro-optic system block diagram

including the scanning and steering devices, optical components, a detector (with associated readout electronics hardware), and signal processing hardware and software. Elements to be modeled may include nonlinear dynamic systems (e.g., target motion); atmospheric effects such as attenuation; optical and detector elements; electronic circuitry and associated noise sources; the signal processing system; and the display system (including elementary eye-brain system modeling in some cases). Figure 1 shows a basic, simplified EO system block diagram.

2.1 Performance Assessment in Electro-Optic Sensor Systems

Determining the performance of an EO sensor system directly is a difficult, time-consuming, and often costly exercise. The functional performance of individual components of the system can often be quantified under laboratory conditions, but the overall performance of the complete system can seldom be assessed in that way. Performance tests on a full system usually require field trials on production or preproduction equipment. Design problems highlighted by trials may demand costly reworking and further trials. It is also noted that trials may cover only part of the operational envelope of the equipment, and so successful completion of trials does not imply a problem-free system.

Field trials involve creating scenarios of interest to assess the performance in different conditions. Such testing requires careful timing of sensor, target, and scene object movements as well as possible decoy and countermeasure deployment for military applications. Weather conditions may provide a further difficulty in that the weather experienced in trials may not represent the conditions within which the sensor must operate.

2.2 The Role of Modeling and Simulation

Mathematical modeling and simulation can address some of the above problems and help to fill the gap between design and the realities of the system performance. Modeling has many functions. For EO sensor systems, a model has a number of possible benefits, including an early assessment of overall performance within or beyond the normal operating envelope, and insight into parameter dependencies and sensitivities which can help in design optimization and minimize design rework.

Two broad classes of model are commonly used in the EO systems field. These are *parametric* models and *image-flow* models [2]. Parametric models can characterize a given system using a relatively small number of key quantities and establish relationships in terms of couplings and interdependencies. Image-flow models describe the effect of EO system elements in terms of images at each stage of the processing chain [3]. Such models allow the effect of optical aberrations and noise sources to be seen rather than to be described mathematically. One advantage of image-flow models is that they provide a convenient test bed for signal processing algorithms.

3. The Concept of a Generic Sensor Model

The potential benefits from adopting a more generic approach to the modeling of EO systems are considerable. Speed of development of new models is possibly the greatest benefit, along with the associated cost savings. Establishing the validity of a complex model in clearly defined steps is another, because this allows model results to be used with greater confidence. Furthermore, traceability and inheritance problems are removed by introducing a generic framework, and wasteful duplication of effort can be avoided [1].

The term "generic: is defined, for the purposes of the work described here, as "general, not specific or special." In the case of EO systems, the similarity of the fundamental components that constitute a system (optical chain, detector, electronics, processing, and display, as shown in Figure 1) provides the basis for the generic representation. From this generic architecture all specific EO systems can be derived [2, 4–7]. Similar approaches involving generic models have been adopted in other fields of application such as gas turbines [8] and power electronic systems [9]. In the last of these application areas (power electronics) the central importance of models and the potential benefits of using standard building blocks in the development of future systems are receiving particular attention [9, 10]. More general issues associated with model reuse, which is of central importance in generic models, have been raised in other recent publications (e.g., [11]).

A *generic sensor model* (GSM) must have a flexible architecture so that different system types may be represented. Although this must be detailed enough to allow some variations between systems, subsystems, or components to be modeled, it must allow a clear understanding of a model's design and permit rapid reconfiguration. Categorizing EO system components to enable any EO application to be described requires an in-depth understanding of real systems. Also, the requirement to describe the EO system with varying degrees of complexity further complicates the design of the generic model.

The methodology has developed through a series of manageable steps in which a highly flexible GSM was created in parallel with more specific models for particular types of EO system. The first of these examples involved a thermal imaging (TI) system. The complete process of building up the GSM was termed a "waterfall" cascade process, in which the full generic functionality of the GSM was added to in stages and proven in each instance via a specific modeling example of a real system. This growing "waterfall" allowed the GSM development to be robust and the risk of the development process to be minimized. Figure 2 illustrates the "waterfall" cascade process.

Initially, the generic model was validated against real data for a specific thermal imaging system [4]. The second stage involved adding to the functionality of the generic model with additional elements for infrared search and track (IRST) systems [4–6]. Once again, the generic model was configured to represent a specific system so that it could be validated. The same approach of deriving a specific model from a

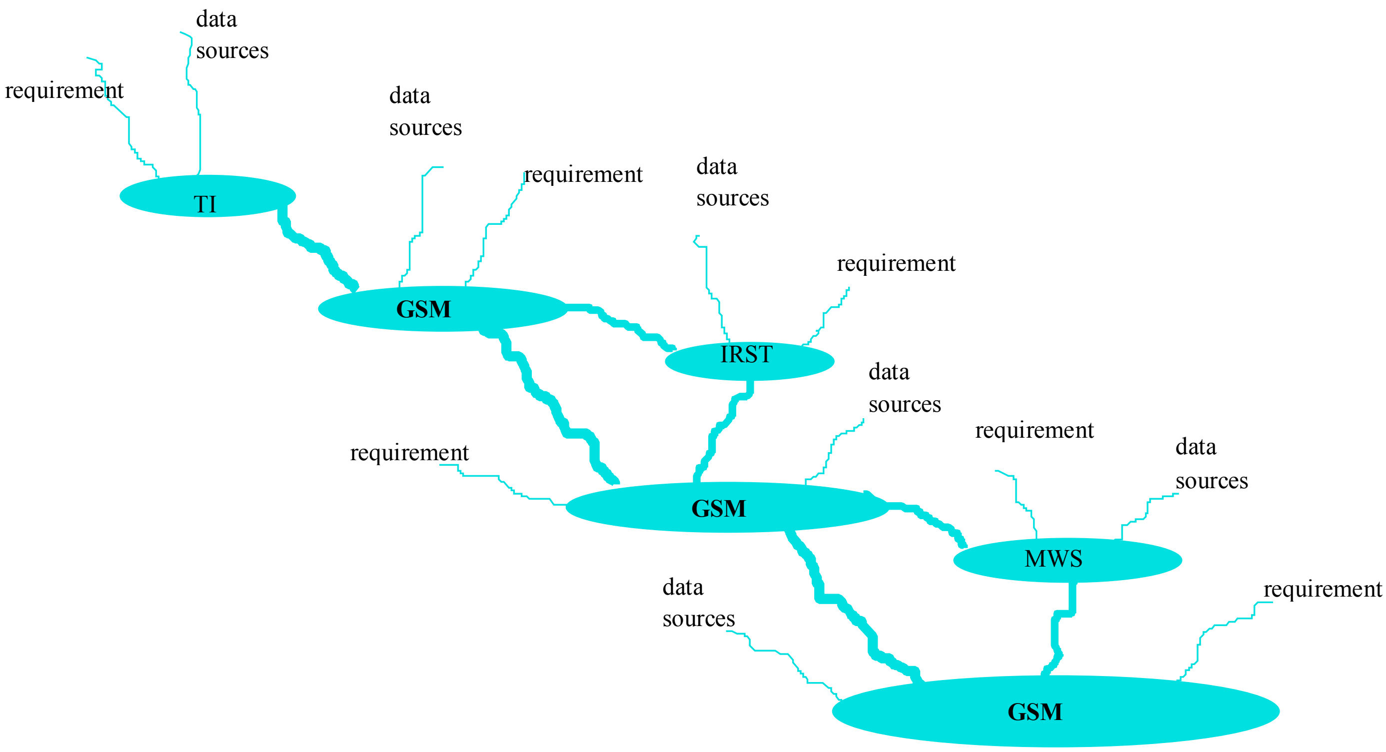


Figure 2. Schematic diagram illustrating approach to generic sensor modeling based on the "waterfall" cascade process and involving creation of models of specific sensor systems (a thermal imager system (TI), an infrared search and track system (IRST) and a missile warning system (MWS)) in parallel with the generic sensor model (GSM)

generic framework, validating it against real data, and then integrating new component models back into the generic sensor model was applied again with a missile warning system (MWS) [4, 7].

This approach has a number of advantages. Firstly, it breaks the problem down into a number of parts. By developing models of specific systems in parallel with the development of the generic model, confidence may be established and new modules within the GSM structure can be added with the full knowledge of the behavior, sensitivities, error bounds, and interfaces required. As the GSM becomes larger, the need to avoid changes to its structure becomes more and more important. Risk is further minimized by the iterative nature of the approach.

Another feature of this approach is that it provides a solution to the problem of how to validate a generic model. Although the full GSM cannot be completely validated, specific configurations of the model can be tested, as can most modules within the generic description. To validate individual modules and specific configurations representing particular EO sensor systems, an appreciation of the model's strengths and weaknesses can be built up, together with an understanding of sensitivities and the valid operational envelope.

Modifications to the generic model can be tested immediately, through regressive testing methods analogous to those used in software code testing, for specific model configurations that have been tested earlier. The investigation of new EO system configurations, not already considered in terms of the generic model, encourages the reuse of submodels and tests the generic philosophy repeatedly. If, at any stage, it is found that the approach fails, then either a fundamental design flaw will have been exposed in the model or a limitation will have been found in the generic approach. Detailed issues of testing and validation of the generic model are discussed more extensively in an associated paper [12].

4. A Methodology and Design for a Generic Electro-Optic Sensor Model

The approach taken was based on simplicity and modularity. Achieving a simple design in a model of this kind is not easy, given the complexity of the problem, the numerous EO applications to be represented, and the varying levels of model detail to be included. However, a simple model design was seen as essential in order to create a truly generic description for a variety of applications.

4.1 Software Tools and the Design Approach

Selective use of software engineering tools assisted in the design process. A balance was struck between stringent software engineering practices developed for safety-critical software and the less structured approach generally taken for simulation. The number and variety of the GSM requirements imposes significant demands and requires a software tool to manage, analyze, and consolidate requirements. The software package RTM (Requirements Traceability Management) [13] was selected for this task. The nature of the GSM lends itself to a top-down functional approach, and the analysis and design tasks were undertaken using Teamwork [14] which implements the Yourdon [15] methodology. This tool provides a traceable path for design changes and, although it provides much information about a system, there are elements missing, such as a mechanism for describing timing information or time-dependent behavior in the system. However, the Yourdon methodology was adopted for the GSM because no approach was identified that could fully describe all aspects of a system design, and time-dependent performance was not an important aspect of this application.

4.2 Requirements Engineering

Requirements engineering is a term used to describe the process of defining requirements for a software system and the analysis needed to produce a software specification. It should provide a reference point for the whole design and helps to ensure that software will be easy to modify.

Every requirement is defined by a clear statement of need and is numbered and cross-referenced. In some cases requirements definition and analysis tasks may be augmented by diagrams known as *conceptual models* [6], which illustrate the main operations of a system.

Once a set of requirements has been established it needs to be validated to reduce the risk of costly errors being introduced at the start of the design process and propagating through the life cycle of the software. The principles of requirements testing and validation are based upon testing, verification, and validation principles that apply generally within software engineering.

The aims and objectives of the GSM were expanded into a set of specific requirements involving a) the model functionality, b) the software tools and framework, c) input and output quantities, d) operational scenarios, e) interfaces, f) documentation, and g) model version control.

4.3 Design Levels for the Generic Model

The GSM design comprises functional and processing representations of the system as well as data flow, logic flow, and screen definitions. Figure 3 shows definitions for the architectural layers and terms. The process of establishing levels in this way has been termed design leveling. This provides a means of relating the many individual mathematical models developed for the GSM to each other and mapping them on to a single, consistent, architectural design. Once consistency has been established across the model, different elements at the same level have the same depth of design detail. This is an iterative process since the need for a particular level of detail within a model may increase or decrease as the architectural design progresses. As illustrated in Figure 3, five levels of software were defined for the GSM, and these are as follows:

- *Context Level* - Defines the environment for the GSM.
- *Functional Block Level* - Establishes groupings of functionality.
- *Module Level* - Provides a collection of linked design features within each functional block.
- *Unit Level* - Each module is divided to a level where the operations can be identified clearly.
- *Component Level* - Each component corresponds to the detailed design description of a task within a unit.

4.3.1 High-Level Design

The high-level functional design of the GSM is shown in Figure 4. In Yourdon terms, the context diagram consists of three objects: the *GSM,* the *user,* and *external models and simulations.* The GSM comprises seven functional blocks and incorporates the graphical user interface.

The first functional block is *system configuration.* Two models constitute this functional block. The *run editor* controls the specifics of the run and the *system configuration editor* assembles the necessary GSM models to fulfil the demands of the run editor.

Automatic checks are carried out by the *data checker* block before a run starts. Simple checks, such as data input type and range, are performed by the *data format checker.* A more thorough check is performed by the *data consistency checker,* which verifies that all of the data entered are self-consistent and compatible for the specified run. Any response from these two modules would be determined by the *data response formatter,* which provides error messages or warnings.

The two main functional blocks of the GSM are the *parametric model* and the *image-flow model.* Both provide three levels of complexity, or tiers. In general, Tier 1 models are used for concept design, have the least mathematical detail, and can incorporate approximations, simplified equations, and rules of thumb. They offer a fast route for generating performance estimates Tier 2 models include more detailed mathematics and provide an

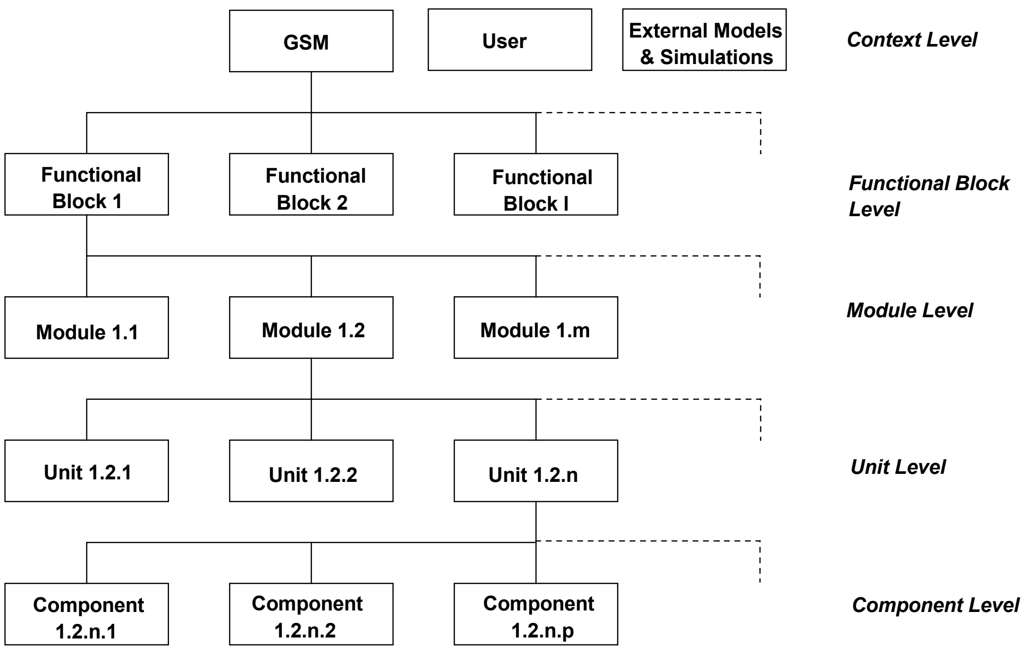


Figure 3. Design terminology definitions for the generic sensor model

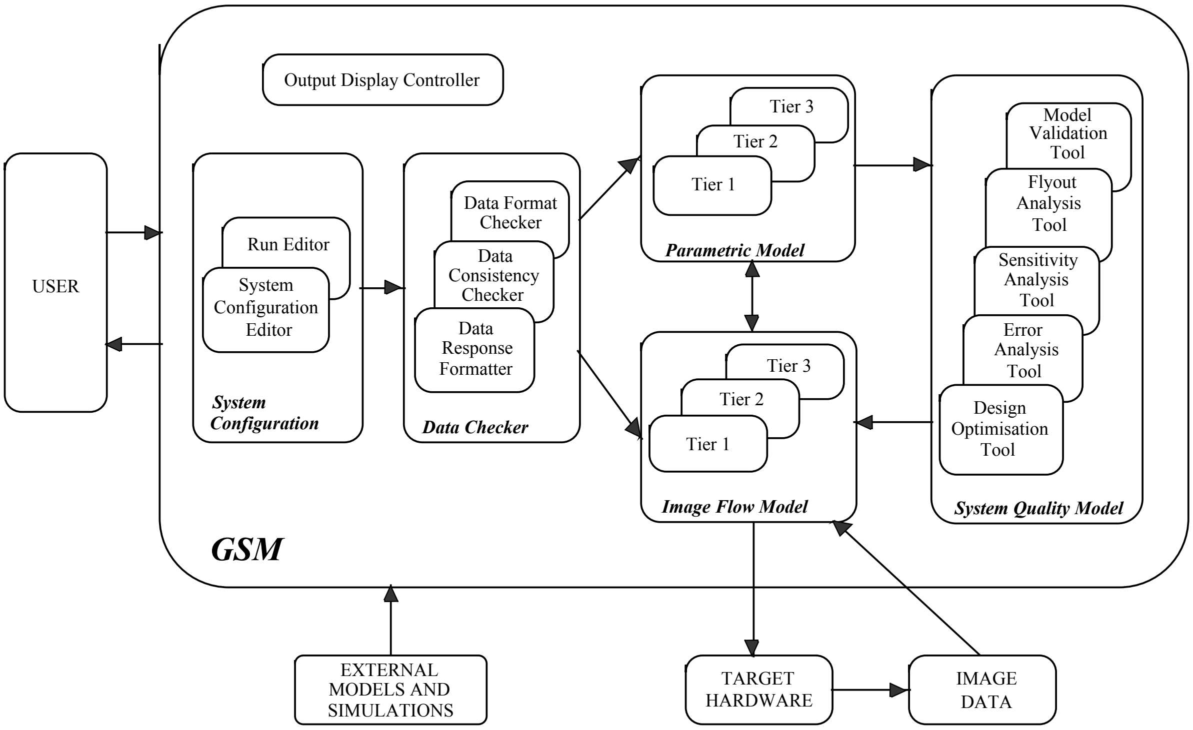


Figure 4. High-level design of the generic sensor model

intermediate-level sensor system model based on design information typically available during the initial design phase. At the level of Tier 3 there is a rigorous mathematical treatment of the components modeled, and this leads to a detailed (high-fidelity) sensor system model based on design information available during and after the detailed design phase.

The parametric and image-flow models share a common high-level design. This is because they are different representations of the same EO systems and functions. A parametric model may be a series of transfer functions and equations that correspond to a statistical description of the behavior of the system. An image-flow model simulates the processes within the EO system by implementing signal and image processing algorithms and produces images as its output. It is appropriate to have cross-coupling links between the parametric and image-flow models so that results of calculations within one model type can be passed to the other, for use as an input or simply to be displayed as an output. One example of this cross-coupling is the extraction of scene metrics (e.g., clutter statistics from real data) from the image-flow model for use in the parametric model. Another example is calculation of the optical blur in a system by the parametric model so that it can then be applied to a scene in the image-flow model to provide visualization of the degradation.

Requirements in terms of the analysis of model results have been addressed in the design of the GSM by including a *system quality model* which involves five modules: *design optimization, sensitivity analysis, error analysis,* a *fly-out analysis tool* and a *validation tool.*

The *design optimization* module allows the user to search for the optimum design solution based on a given starting configuration. It should allow an EO system design to be formulated using the configuration and data bounds specified by the user. A variety of search strategies can be used.

The *sensitivity analysis* module automatically examines the stability of a system design with respect to environmental variables, system variables, or component degradation effects. The *error analysis* module builds upon the sensitivity analysis module output information to provide an indication of the errors associated with model results, for given levels of uncertainty in terms of system variables and components.

The *fly-out analysis tool* allows the GSM to carry out operational analysis involving Monte Carlo simulation studies. Such studies help in establishing appropriate operating environments for the sensor system.

The *validation tool* allows model results to be compared with measurement data on file. This module produces a number of metrics that quantify the validity of the model over a specified operating range.

There are two further functional blocks within the GSM. These are the *file manager,* which provides all of the default parameters from files but is not shown in Figure 4, and the *output display controller,* which is included in the block diagram and handles all aspects of display formatting of output data. Finally, links are provided to allow hardware-in-the-loop testing in association with the image-flow model.

4.3.2 Parametric Model Design

The parametric model involves four modules. These are the *environment* module, the *sensor head* module, the *target processing* module and the *display and human interface* module; they are linked in a sequential manner, as illustrated in Figure 5.

The shaded bands in Figure 5 represent the four modules specified above, and the blocks underneath are the units that make up each module. A user is given the option of by-passing one or more units or modules when specifying a run, provided the action is permissible. Data for each unit may be entered by the user or default values may be chosen.

4.3.3 Image-Flow Model Design

The high-level architectural design of the image-flow model is identical to the design for the parametric model. This allows the commonality between the models to be exploited and code to be reused as much as possible. It also provides a one-to-one mapping, which helps in testing, internal verification, and external validation. However, at lower levels in the design, greater interaction of components and feedback of data is possible in the image-flow model and is a requirement of many of the processing algorithms.

The use of valid input data is as important for the image-flow model as it is for the parametric model, but the image-flow model input data are generally more difficult to obtain. An image-flow model is used to test the performance of image processing and tracking algorithms, and the demanded level of scene realism (in terms of radiometric accuracy) for good performance prediction is extremely high. The most accurate performance figures will be achieved by using real data recorded by an EO system. That imagery would serve as input data directly to the processing module of the GSM since it would already contain all of the atmospheric and sensor effects within it. Synthetic images produced by the image-flow model must be based on the analysis of real data of this kind.

4.3.4 Graphical User Interface Design

One important element of a user-friendly generic model is the user interface, and an early decision was taken to implement a graphical user interface (GUI). Any GUI should be tailored to the needs of the user. This usually means that technical aspects of the software are hidden from the user, but in the case of mathematical models this is less likely to be so, as the models will be run generally by expert users. The GUI is linked closely to the design and optimization of the model itself because changes to the structure

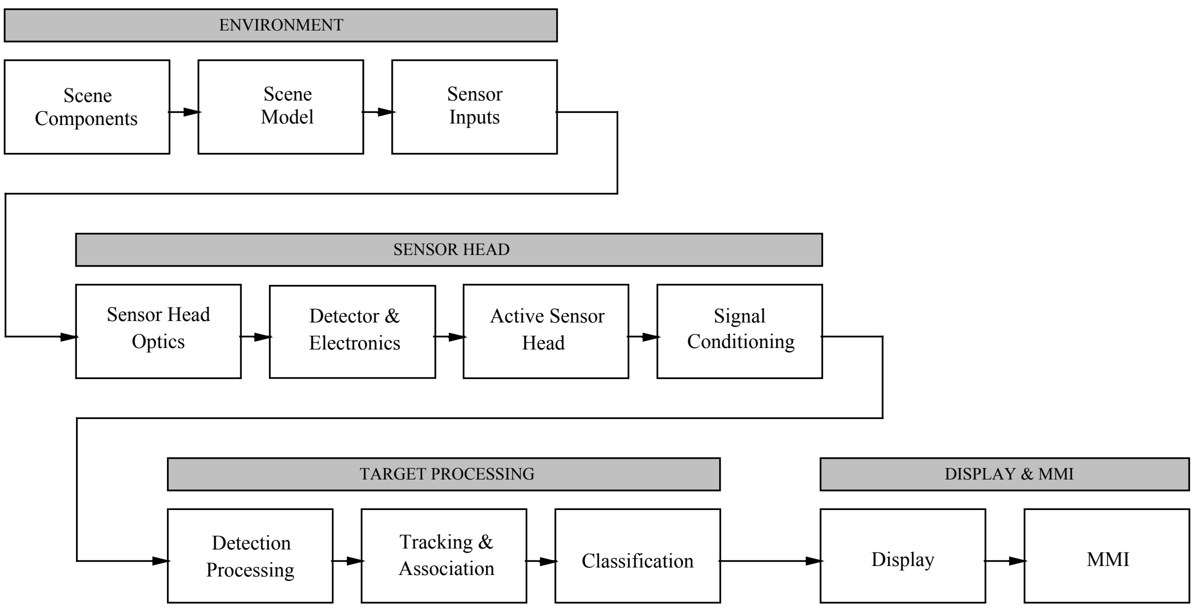


Figure 5. Architecture of the parametric model

and content of the GSM are likely to require changes to the GUI.

The approach taken to GUI design to minimize design rework was to separate it from the main model. Screens were not implemented until there was some stability in the model design and sets of input and output parameters had been established.

4.4 Implementation

The GSM allows ideas and designs to be developed and tested. Its principles are independent of software and hardware restrictions and should still be applicable when new generations of computers and software environments become available.

The main criterion for the GSM software coding language and environment was that it should have a powerful mathematical and processing capability and have a large user community so that the GSM would be widely accepted, understood, and supported. Speed of calculation was not, however, seen to be a critical driver because the model need not run in real time.

A personal computer (PC)–based package was chosen because of the processing capabilities now afforded by such machines and their wide availability. Several software packages were reviewed and a subset was assessed against specific criteria for the GSM. The choice of development environment and language of the initial GSM implementation was MATLAB. Although a number of other products gave better performance for certain types of modeling task, such as image processing, MATLAB was judged to give the best overall solution. Factors of particular significance include the large set of in-built functions, the multi-platform nature of the product, and its ability to generate C code for applications for which processing speed is an issue.

5. Parametric and Image-Flow Modeling Examples

5.1 Parametric Modeling Examples

The automatic detection of targets by an EO system and the subsequent processing to classify, track, and prioritize them is a complex procedure that involves the interaction of a number of different real-time algorithms and optimized filters. Modeling such a processing chain in a parametric sense is important for examining couplings and interdependencies and for establishing key relationships. In simple terms, a target is detected using some filtering mechanism with a thresholding scheme. Following further signal processing it may then be declared as a threat and tracked before being classified.

Detection requires the separation of target and background signals through filtering. Modeling of this process can be simplified by considering the probability of a target being detected, given that it has a specific signal-to-noise ratio (SNR) and that a particular threshold-to-noise ratio (TNR) has been set. The variation of the target and background signals means that it is possible that a spike in the background could exceed the threshold, thus triggering a false alarm. The TNR is normally set to maximize the probability of detecting a target (the detection probability) while minimizing the false alarm rate. The declaration probability is the probability of a target being declared as a threat. This is dependent on the signal processing logic implemented in the algorithm, and many schemes are possible.

It should be noted that, in the modeling of different signal processing systems for detection and declaration, it is possible that the probability of declaration may be found to be larger than the probability of detection at a specific range. This depends on the signal processing schemes considered and the modeling approach used. When such a situation arises it means that, for a given declaration range, the required signal-to-noise ratio (SNR) can be reduced. This is illustrated in Figure 6, which represents typical output from a parametric model and illustrates the variation of detection probability (dashed line) and declaration probability (solid line) as a function of range for a given set of target, atmospheric, and sensor parameters.

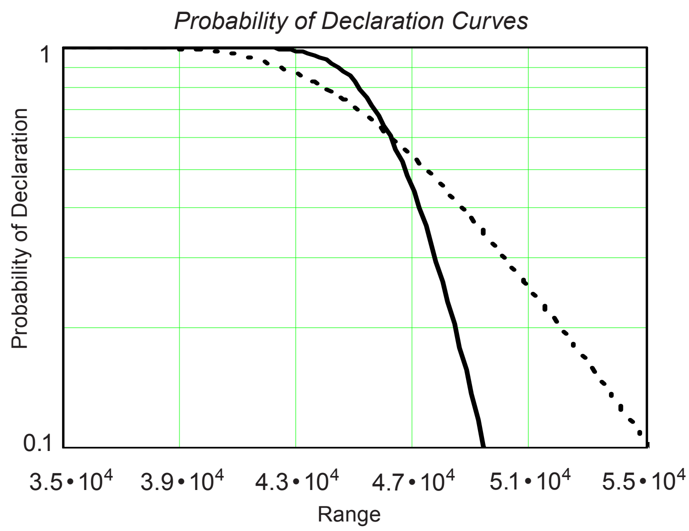
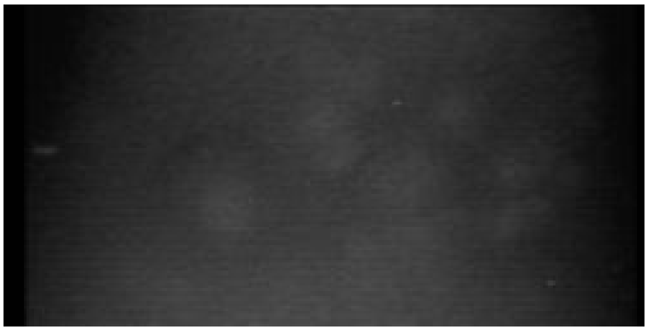
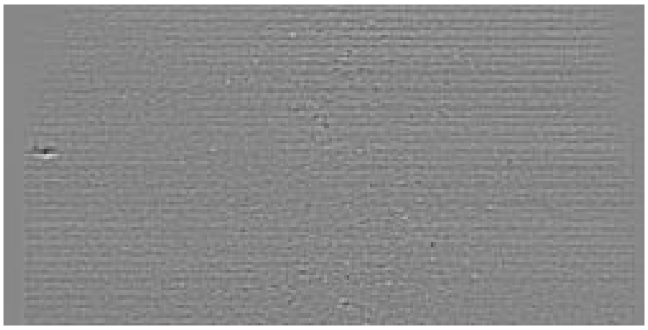


Figure 6. Example of a parametric model output; the solid line represents the probability of a target being declared as a threat (declaration probability) while the dashed line indicates the detection probability





Figures 7 and 8. Image-flow model output: the unprocessed image is on the top (Figure 7) while the image on the bottom (Figure 8) shows the effect of spatial filtering and thresholding and indicates clearly the presence of an object (the aircraft) towards the left-hand edge of the image.

5.2 Image-Flow Modeling Examples

Examples of the use of the image-flow analysis component of the GSM are illustrated in Figures 7 and 8. Figure 7 shows a poor-quality thermal image, which includes an aircraft that is virtually invisible. Figure 8 illustrates the effect of spatial filtering and thresholding on the image as part of the detection processing chain. Such image-processing operations can be used not only for improving the visual appearance of an image but can also provide performance data for the parametric model.

6. Some Examples of Use of the System Quality Model

The *system quality model* involves five modules, and any combination of these can be selected by the user to be included in a run. The design optimization tools and the sensitivity analysis tools are particularly important, and their use will be illustrated through examples.

6.1 Use of the Design Optimization Tools

Most engineering design problems require optimization in which costs and benefits are traded to allow an improved solution to be found. The first component within the optimization module is the *sensor optimization* component, which is designed to perform a search over a parameter set identified by the user and return optimal parameter values for the design space specified. The second component is for *cost optimization* and allows the engineering reality of a given technical solution to be reviewed by assessing the cost and risk associated with any performance gain promised.

As an example of cost optimization consider four design parameters that could be candidates for adjustments leading to a possible improvement in overall performance of an EO system in terms of signal-to-noise ratio. These could be as follows:

- Optical system performance;
- Detector performance;
- Electronic system bandwidth adjustment;
- Signal processing performance through use of an improved clutter suppression algorithm.

Cost and risk values could be associated with each of these four design parameters and, in each case, these will be a function of the performance improvement required. For example, improvements in each of these areas could be achieved, but in most cases this could involve extra cost and risk because of the development time required and uncertainties associated with the development task. The availability of this tool should, for example, allow a project manager to examine the impact of a design deficiency or provide justification for further design work.

The optimization method is chosen from a list of candidate methods. This facility was developed as part of the GSM to establish the optimum combination of components or system parameters within predefined parameter ranges. A score is determined at each iteration of the model, based on a user-defined rating scheme.

Several search strategies have been assessed [2, 4], including exhaustive search methods, heuristic search methods, methods based on the use of Hopfield networks (a specific form of artificial neural network), and methods involving genetic algorithms. Of these approaches the exhaustive search method was a benchmark against which other methods could be compared. Because it is so computationally intensive and time-consuming it could be used only for problems that were of relatively low complexity.

Two heuristic (rule-based) search methods have been applied [2, 4]. One of these was a steepest-ascent hill-climbing algorithm with enhancements (backtracking and jumping) in order to help to avoid known pitfalls of this approach. Backtracking was added to ensure that local maxima were not declared as the global maximum, and a random jump was incorporated to avoid stagnation at plateaux. The second heuristic strategy searches concentric rectangular areas of interest, storing any maxima found until the limits of the search space are reached [4]. Hill-climbing, or another fine search technique, can then be applied around these maxima to determine the global maximum.

A restricted data set was established to allow testing of the chosen strategies. Table 1 lists the five quantities available for adjustment and Table 2 lists five performance metrics to be optimized.

Weighting factors were applied to each parameter to indicate the level of importance placed on each. Allowable ranges for each input parameter were defined and a baseline value was set. Cost functions were also set for each input parameter to allow non-technical considerations to be taken into account in the optimization process. Desired performance values were also specified, and acceptable ranges for each were declared as constraints (Table 2).

An overall scoring method was used involving an objective function that considered performance demands, parametric and cost ranges, weightings, and parameter constraints. Although this data set is much smaller than the set that would be required to optimize a full EO system the search space is, nevertheless, considerable and provided a useful test of the different optimization methods.

Table 3 provides a summary of the results for a number of techniques. Although the exhaustive search method was included, it serves only to provide a benchmark against which the other methods can be compared. The table shows the maxima found by each method, and the performance of each method, in terms of accuracy and processing time, is then compared with results from the exhaustive search. The modified steepest-ascent hill climbing algorithm performed well and found the global optimum while the second heuristic method, which was based on a concentric area search strategy and subsequent hill climbing, also performed well. Both of these methods involved processing times which were approximately 1000 times smaller than those for the exhaustive search method. The performance of the Hopfield network was relatively disappointing due to its known tendency to find spurious equilibrium states and halt on these points that are not states with minimum energy and thus do not represent the overall optimum solution [16]. Only 65% of equilibrium points found

Table 1. Test input parameters for optimization

Design Parameter Name	Baseline Design Parameter Estimate	Weighting Factor	Allowable Range	
			Minimum	Maximum
Sampling efficiency	0.8	1	0.5	0.9
Noise equivalent temperatue difference (NETD)	30mK	1	28mK	32mK
Effective focal length (EFL)	0.06m	0.3	0.04m	0.08m
Threshold-to-noise ratio (TNR)	5	0.5	4	6
Classifier efficiency	0.75	0.8	0.5	0.9

Table 2. Test output goals for optimization

Performance Parameter	Baseline Performance Estimate	Performance Requirement	Weighting Factor	Parameter Constraints
Signal-to-noise ratio	4	5	0.7	min. 2
Probability of detection	0.85	0.95	0.9	0.6–1
Probability of declaration	0.8	0.9	1	0.6–1
Probability of false alarm	0.01	0.001	0.8	$0–10^{-5}$
False-alarm rate (FAR) (per hour)	10	10	1	max. 15

Table 3. Optimization test results: the figures for relative processing performance show processing time improvement factors relative to the exhaustive search method

Search Strategy	Maxima Found (Top Ten)	Maximum Score (Relative)	Relative Processing Performance
Exhaustive	100%	1	1
Heuristic method 1 (hill-climbing with constraint satisfaction)	100%	1	951
Heuristic method 2 (neighborhoods approach)	100%	1	1072
Hopfield network	65% convergence to global maximum	1 (with repeated runs)	26
Genetic algorithm	Average accuracy: 91% of optimum solution	0.91	6

represented the global optimum, but repetition of the run many times did show that the Hopfield network could find the optimum solution reliably. The overall performance efficiency of this algorithm was thus found to be relatively poor. The genetic algorithm provided excellent results with convergence, on average, after forty generations. However, the run-time for the genetic algorithm was greater than for the other methods.

6.2 Use of the Sensitivity Analysis Tool

Sensitivity analysis provides a way of examining the effect of system or sensor parameters on one or more of the overall performance metrics. The *sensitivity analysis tool* is designed for use together with the parametric descriptions within the GSM. Taking user-specified input parameter values, the analysis tool uses the transfer functions of the parametric model to investigate variations of output parameters. Results are presented both graphically and numerically to provide an understanding of the relative sensitivities within the system.

Two separate components were designed for the toolbox: *scene sensitivity* and *sensor sensitivity.* Scene sensitivity examines the sensitivity of the sensor performance to external factors such as target signal strength and dynamics while sensor sensitivity allows investigation of effects of sensor parameter variations on the overall performance.

The analysis carried out by each component is the same. The user is presented with sets of input parameters for the Tier 1 model. Any parameters may be varied by a positive or negative percentage from baseline values. Those parameters not selected for variation are held at their baseline values. All results are written to file, from which they may be retrieved and manipulated, depending on the options chosen.

Figure 9 shows typical results, in the form of a polar diagram, of a sensitivity analysis carried out to evaluate the effect of a 25% variation in radiant intensity, atmospheric attenuation, noise equivalent irradiance (NEI), detector sampling efficiency and threshold to noise ratio (TNR) on target detection probability. In this diagram dashed lines represent the nominal value (0% deviation) and the solid lines represent the variation about that value.

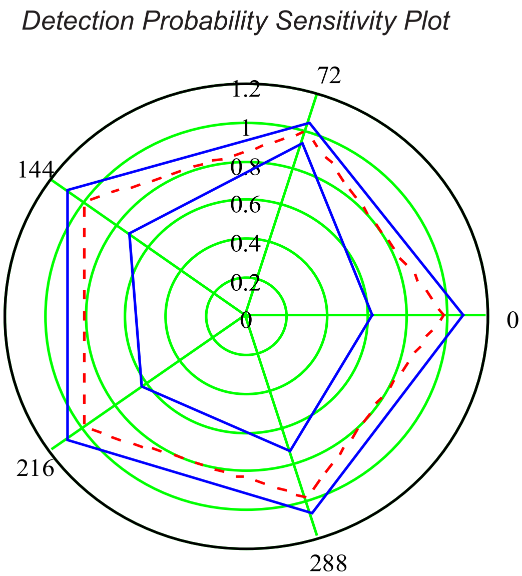


Figure 9. Example of a polar plot resulting from a detection probability sensitivity analysis. Here dashed lines represent the nominal value (0% deviation) and solid lines indicate the variations of detection probability about the nominal value (unity) for 25% changes of each of five input quantities. The five quantities represented on this diagram are radiant intensity (on axial line at 0 degrees), atmospheric attenuation (72 degrees), noise equivalent irradiation (144 degrees), detector sampling efficiency (216 degrees), and threshold to noise ratio (288 degrees).

It can be seen from the sensitivity diagram that radiant intensity (shown on the plot by the radial line at 0 degrees) and sampling efficiency (the line at 216 degrees) have the greatest effect on the probability of detection. It can also be seen that detection of a target is less likely to be adversely affected by a change in atmospheric attenuation (the line at 72 degrees) than by an equivalent percentage change in threshold-to-noise ratio (the line at 288 degrees). It should be noted that since the nominal values in this plot all represent detection probabilities of one this sensitivity analysis is meaningful, in this particular case, for changes that reduce the detection probability.

7. Discussion

Making a model generic in the field of electro-optic systems proved difficult. The first step was to identify the truly essential requirements and then, second, to establish a framework that would meet these requirements whilst providing flexibility and adaptability. The third feature of the chosen approach was to make the generic sensor model concentrate on a relatively small subset of specific sensor systems. There are two advantages to this third aspect of the approach. While it provides concrete examples of working models that can be used to guide future developments and enhancements, it still provides considerable flexibility that can be tailored easily to the specific needs of individual programs.

Using the generic approach, systems may be modeled at different levels of detail and complexity at different stages in the product life-cycle. A less complex model is appropriate at the preliminary design stage of a project because only rough performance estimates are required and little information is available to allow a more detailed model to be developed. In contrast, by the end of the project highly detailed models that incorporate a large amount of design knowledge are possible and should be available to aid performance optimization and system maintenance

The traditional engineering flow involving requirements definition, top-level design, detailed design, coding, test, and validation was applied to the GSM. However, the need to tailor the sequence to the needs of the model development program quickly became evident. One of the first features to emerge was the fact that generation of the requirements definition for a generic model is a difficult task. Not only is the number of requirements very large but also many are not fully defined at the initial stage of model development and not all are of equal importance. The initial focus on a few specific systems helped considerably and allowed priority issues to be identified. The grouping of these issues and the flow-down to a structured analysis also proved to be successful because it helped to define the architecture of the model. In terms of project time lines, the requirements analysis is not considered to be complete and is an ongoing activity. To date, all new requirements imposed on the generic model have been accommodated without difficulty.

8. Conclusions

Mathematical and computer-based modeling has an important role in the design and development of electro-optic systems. It provides an insight into system behavior, sensitivities, and dependencies before a system is built so that its performance may be optimized and costs minimized. Computer-based modeling also enables trade-off studies to be automated and controlled and different configurations of system to be tested in safety.

The main factors of significance in the model design and implementation process include the fact that modeling must be tied to the complete project life cycle and a set of models of different mathematical complexity is needed to fulfil the modeling needs of a project throughout its life cycle. Also, a structured approach to requirements analysis and design is essential, and the model design process should be based on rapid prototyping. It should support iterative development using appropriate software tools and a suitable environment.

Model validation issues are very important for any work involving the practical application of mathematical and computer-based models. The generic nature of the model in this case gives rise to special questions that lie beyond the scope of this paper and are discussed elsewhere [13, 17].

The main conclusion is that a generic EO system model is possible. It may also be concluded that parametric representation of systems provides useful performance estimations but is limited by the statistical approach taken to the complex processing chain, while image-flow models of scenes and the EO system processing are required to fully describe the system performance, especially if real data are fed directly into the processing module of an image-flow model. The provision of these different model types (i.e., parametric and image-flow) within the generic model can thus provide valuable insight that could be lacking in the absence of such cross-coupling.

Overall, a novel approach to tackling the complex problem of EO sensor systems modeling has been demonstrated successfully. The research provides a solution for the EO systems community in which modeling supports the systems engineering life cycle and allows predictions and analysis of system performance to be made using a truly flexible and generic framework. The benefits of this approach, including design reuse and rapid development, have been demonstrated through specific case studies.

9. References

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Author Biographies

Dr. Moira Smith B.Eng., Ph.D., MRAeS, MIEE. *Dr. Moira Smith is director of the technology consultancy company Waterfall Solutions Ltd., which specializes in image processing, algorithm and software development, and mathematical modeling, primarily for the defense industry. Heavily involved in the research and development of modeling and processing systems at an international level, Dr. Smith provides subject-matter expertise to the U.K. Ministry of Defence in this area and also leads training courses on data and image fusion. She has also authored papers on modeling and validation, chaired international conferences on EO systems modeling and processing, and is currently on SPIE's security and surveillance organizing committee.*

Dr. Smith has a degree in avionics and a Ph.D. Prior to Waterfall Solutions she worked for Thales Optronics' Algorithm Group developing EO processing algorithms and mathematical models for programs including Eurofighter and Fast Jet MWS. Dr. Smith also previously worked for Logica's Aerospace and Defense Division developing real-time avionics software for helicopters and spacecraft systems.

Dr. David Murray-Smith, B.Sc.(Eng.), M.Sc., Ph.D., FIEE. *David Murray-Smith is an Emeritus Professor of the University of Glasgow. He is also an Adjunct Research Professor within the College of Engineering, Computer Science, and Construction Management at California State University, Chico. Until his retirement in 2005 he was Professor of Engineering Systems and Control in the Department of Electronics and Electrical Engineering at the University of Glasgow.*

Dr. Murray-Smith's career began as a development engineer working on navigation systems with Ferranti Ltd., Edinburgh. His move to academic employment in the late 1960s led, over a period of about forty years, to active involvement in research in a number of different application areas including helicopter modeling and system identification, flight control, marine vehicle control, and to broader interests in simulation methodologies and model validation.

David Murray-Smith has a B.Sc.(Eng.) in electrical engineering and also M.Sc. and Ph.D. degrees.

Dr. Duncan Hickman B.Sc., M.Sc., Ph.D., M.Inst.P. *Currently Chief Engineer for Waterfall Solutions Ltd., Dr. Hickman has responsibility for both design and engineering processes within the company, as well as business and technology strategy for future products. Dr. Hickman has considerable experience of major defense programs, including Eurofighter, TRACER, and FRES, and before joining Waterfall Solutions he was the Engineering Manager for the SeaWolf Mid-Life Update program. His expertise covers a wide range of technical areas, including electro-optical systems design and development, modeling, validation, processing algorithms and systems engineering, as well as group, project, and strategic management.*

Dr. Hickman holds a B.Sc., M.Sc. and Ph.D. in physics and is a Chartered Physicist. Before joining Waterfall Solutions he worked for BAE Systems Advanced Technology Centre, Oxford University, Matra Marconi Space Systems, Thales Optronics, and BAE Systems Insyte.